# IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

**APPELLANT:** Alex Nugent **EXAMINER:** Mai T Trai
**SERIAL NO.:** 10/748,631 **GROUP:** 2129
**FILED:** 12/30/2003 **ATTY DKT NO.:** 1000-1216
**TITLE:** **APPLICATION OF HEBBIAN AND ANTI-HEBBIAN LEARNING TO NANOTECHNOLOGY-BASED PHYSICAL NEURAL NETWORKS**

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**Please forward all correspondence to:**
ORTIZ & LOPEZ, PLLC
Patent Attorneys
P.O. Box 4484
Albuquerque, NM 87196-4484

**CERTIFICATE OF MAILING**

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Kermit D. Lopez

**Kermit D. Lopez** **April 16, 2007**

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## APPEAL BRIEF FILED UNDER C.F.R. §1.192
## AMENDED BY APPELLANTS' TO COMPLY WITH 37 CFR 41.37(C)

Dear Sir:

In response to the Notification of Non-Compliant Appeal Brief dated January 30, 2006, please accepted this amended brief with the corrections provided herein to include items required under 37 C.F.R. 41.37(c).

This replacement brief is being submitted in triplicate.

## I. REAL PARTY IN INTEREST

Alex Nugent is the real parties in interest in the present invention, and is also the "Appellant" entitled to bring forward this appeal.

## II. RELATED APPEALS AND INTERFERENCES

There are currently no related appeals and/or interferences related to the above-referenced patent application.

## III. STATUS OF CLAIMS

This Appellant appeals the final rejection to claims 1-20 as set forth in the Final office action dated November 2, 2006 and repeated in the "Advisory Action Before the Filing of an Appeal" dated January 8, 2007. Claims 1-20 therefore constitute the appealed claims.

The application was originally filed with 20 claims. In the first office action dated June 29, 2006, claims 1-20 were rejected. Appellant responded on August 14, 2006 to the first office action with an amendment in which original claims 1, 11, 15, 16, 17, 18 were amended. In the second and final office action dated November 2, 2006, claims 1-20 were again rejected by the Examiner. The Appellant responded to the final office action on November 30, 2006 with a minor amendment to claim 18 and the specification and supporting remarks wherein the Appellant distinguished the cited prior art from Appellant's claims.

In an "Advisory Action Before the Filing of an Appeal" dated January 8, 2007, the Examiner denied entry of the proposed amendments and maintained the rejection of claims 1-20 and indicated that "due to the usual limited allowed time after a final office action, Examiner only responds to certain issues raised". In the Advisory Action dated January 8, 2007, the Examiner did not respond to the amendments and remarks made in the office action of November 30, 2006 with respect to the 102 and 103 rejections, but instead stated only that "applicant's arguments regarding 102 and 103 rejections have all been responded in the final

office action" without addressing the arguments and amendments made by the Appellant in the office action of November 30, 2006.

## IV. STATUS OF AMENDMENTS

The amendment of claims 1, 11, 15, 16, 17, 18 by Appellants prior to the Final office action and the amendment to claim 8 after the Final Office Action are the claims that are now the subject of the appeal. Claims 1-20 remain pending in the appealed application.

The final rejection of claims 1-20 is the subject of this appeal. The Appellant also requests entry of the minor amendments to both the specification and claims made in the response filed on November 30, 2006 to the final office action.

## V. SUMMARY OF CLAIMED SUBJECT MATTER

The invention claimed in independent claims 1, 11, and 17 is directed toward a system composed of a physical neural network configured utilizing nanotechnology. Dependent claims 2-10 (which are dependent upon independent claim 1), claims 12-16 (which are dependent upon independent claim 11), and claims 18-20 (which are dependent upon independent claim 17) also teach various aspects and features of such a physical neural network based on nanotechnology. The physical neural network of claims 1-20 is therefore shown and described with respect to FIGS. 1-40 and pages 18-96 of Appellant's specification. The language specifically distinguishing the independent claims 1, 11, and 17 from the art of record is underlined below:

1. A <u>system</u>, comprising:

a <u>physical</u> <u>neural network</u> configured utilizing <u>nanotechnology</u>, wherein said physical neural network comprises a <u>plurality</u> of <u>nanoconductors</u> <u>suspended</u> and <u>free</u> to <u>move about</u> in a <u>dielectric medium</u> and which form <u>neural connections</u> between <u>pre-synapti</u>c and <u>post-synaptic</u> <u>components</u> of said physical neural network; and

a <u>learning mechanism</u> for <u>applying</u> <u>Hebbian</u> <u>learning</u> to said physical neural network.

11. A <u>system</u>, comprising:

a <u>physical neural network</u> configured utilizing <u>nanotechnology</u>, wherein said physical neural network comprises a <u>plurality</u> of <u>nanoconductors</u> suspended and <u>free</u> to <u>move about</u> in a <u>dielectric medium</u> and which form <u>neural connections</u> between <u>pre-synaptic</u> and <u>post-synaptic</u> components of said physical neural network; and

a <u>learning mechanism</u> for <u>applying</u> <u>Hebbian</u> <u>learning</u> to said physical neural network wherein said learning mechanism utilizes a <u>voltage gradient</u> <u>or</u> <u>pre-synaptic</u> and <u>post-synaptic</u> <u>frequencies</u> thereof to implement <u>Hebbian</u> <u>or</u> <u>anti-Hebbian</u> <u>plasticity</u> within said physical neural network.

17. A <u>system</u>, comprising:

a <u>plurality</u> of <u>molecular conductors</u> <u>disposed in and free to move about</u> <u>within</u> a <u>dielectric medium</u> comprising a <u>dielectric solvent</u> or a <u>dielectric solution</u>;

<u>at least one input electrode</u> in <u>contact</u> with said <u>dielectric medium</u>; and

<u>at least one output electrode</u> in <u>contact</u> with said <u>dielectric medium</u>, wherein said plurality of molecular conductors form <u>physical</u> <u>neural connections</u> <u>when</u> said dielectric medium is <u>exposed</u> an <u>electric field</u> <u>across</u> said at least one input electrode and said at least one output electrode, such that said physical neural connections can be <u>strengthened</u> or <u>weakened</u> depending upon a <u>strengthening</u> or <u>weakening</u> of said <u>electric field</u> <u>or</u> an <u>alteration</u> of a <u>frequency</u> thereof.

The invention shown and claimed in each of the above claims is explicitly described in the specification with respect to FIGS. 1-40 enables a plurality of nanoconductors suspended and free to move about in a dielectric medium and which form neural connections between pre-synaptic and post-synaptic components of the physical neural network. The system described with respect to FIGS. 1-40 further includes a learning mechanism for applying Hebbian learning to the physical neural network. The learning mechanism can utilize a voltage gradient to implement Hebbian plasticity within the physical neural network. Hebbian learning is based on <u>Hebbian</u> theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Hebbian learning is discussed in greater detail herein.

The learning mechanism described with respect to FIGS. 1-40 of Appellant's specification also can utilize voltage gradient dependencies associated with physical neural network to implement Hebbian learning within the physical neural network. The learning mechanism can additionally utilize pre-synaptic and post-synaptic frequencies to provide Hebbian learning within the physical neural network. The

learning mechanism can also use a voltage gradient to implement anti-Hebbian plasticity within the physical neural network. Such a learning mechanism can also utilize voltage gradient dependencies associated with physical neural network to implement anti-Hebbian learning within the physical neural network. The learning mechanism can also use pre-synaptic and post-synaptic frequencies to provide anti-Hebbian learning within the physical neural network. The nanoconductors can be, for example, nanotubes, nanowires, nanoparticles and the like.

The Appellant's invention illustrated in FIGS. 1-40 is also directed toward a system, comprising a physical neural network configured utilizing nanotechnology, wherein the physical neural network comprises a plurality of nanoconductors suspended and free to move about in a dielectric medium and which form neural connections between pre-synaptic and post-synaptic components of the physical neural network. The system includes a learning mechanism for applying Hebbian learning to the physical neural network wherein the learning mechanism utilizes a voltage gradient or pre-synaptic and post-synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within the physical neural network. The nanoconductors can be, for example, nanotubes, nanowires, nanoparticles and the like. The dielectric medium can be a dielectric liquid. The nanoconductors form physical neural connections when the dielectric medium is exposed to an electric field, such that the physical neural connections can be strengthened or weakened depending upon a strengthening or weakening of the electric field or an alteration of a frequency thereof.

Appellant's invention illustrated in FIGS. 1-40 is also directed toward a system that includes a plurality of molecular conductors disposed in and free to move about within a dielectric medium comprising a dielectric solvent or a dielectric solution; at least one input electrode in contact with the dielectric medium; and at least one output electrode in contact with the dielectric medium, wherein the plurality of molecular conductors form physical neural connections when the dielectric medium is exposed an electric field across the at least one input electrode and the at least one output electrode, such that the physical neural connections can be strengthened or weakened depending upon a strengthening or weakening of the electric field or an alteration of a frequency thereof.

The physical neural network described in Appellant's specification with respect to FIGS. 1-40 can include the plurality of molecular conductors disposed within a dielectric medium comprising a dielectric solvent or a dielectric solution, the at least one input electrode in contact with the dielectric medium, and the at least one output electrode in contact with the dielectric medium. Such a system further includes a learning mechanism for applying Hebbian learning to the physical neural network wherein the learning mechanism utilizes a voltage gradient or pre-synaptic and post-synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within the physical neural network. The physical neural network is configured as an integrated circuit chip utilizing nanotechnology.

In order to appreciate the context in which Appellant's independent claims 1, 11, and 17 and respective dependent claims 2-10, 12-16, and 18-20 are based, Appellant believes it would be helpful to review the unique concepts outlined in pages 18-96 of Appellant's specification.

The physical neural network described and disclosed in Appellant's specification with respect to FIGS. 1-40 is different from prior art forms of neural networks in that the disclosed physical neural network does not require computer calculations for training, nor is its architecture based on any current neural network hardware device.

Appellant's physical neural network generally possesses two basic components. First, such a physical neural network should have one or more neuron-like nodes that sum a signal and output a signal based on the amount of input signal received. Such a neuron-like node is generally non-linear in output. In other words, there should be a certain threshold for input signals, below which nothing can be output and above which a constant or nearly constant output is generated or allowed to pass. This is considered the basic building block of all neural networks, and can be accomplished by an activation function. The second requirement of Appellant's physical neural network is the inclusion of a *connection network* composed of a plurality of interconnected electrodes (i.e., nanoconnections).

FIG. 1 of Appellant's specification illustrates a graph 100 illustrating a typical activation function that can be implemented in accordance with the physical neural network of Appellant's invention. Note that the activation function need not be non-

linear, although non-linearity is generally desired for learning complicated input-output relationships. The activation function depicted in FIG. 1 comprises a linear function, and is shown as such for general edification and illustrative purposes only. An activation function may also be non-linear.

As illustrated in FIG. 1, graph 100 includes a horizontal axis 104 representing a sum of inputs, and a vertical axis 102 representing output values. A graphical line 106 indicates threshold values along a range of inputs from approximately -10 to +10 and a range of output values from approximately 0 to 1. As more neural networks (i.e., active inputs) are established, the overall output as indicated at line 105 climbs until the saturation level indicated by line 106 is attained. If a connection is not utilized, then the level of output (i.e., connection strength) begins to fade until it is revived. This phenomenon is analogous to short term memory loss of a human brain. Note that graph 100 is presented for generally illustrative and edification purposes only and is not considered a limiting feature of the present invention.

The neuron-like node can be configured as a standard diode-based circuit, the diode being the most basic semiconductor electrical component, and the signal it sums can be a voltage. An example of such an arrangement of circuitry is illustrated in FIG. 2, which generally illustrates a schematic diagram illustrating a diode-based configuration as a neuron 200, in accordance with an embodiment of the present invention. The use of such a diode-based configuration is not considered a limiting feature of the present invention, but merely represents one potential arrangement in which the present invention can be implemented.

Although a diode may not necessarily be utilized, its current versus voltage characteristics are non-linear when used with associated resistors and similar to the relationship depicted in FIG. 1. The use of a diode as a neuron is thus not considered a limiting feature of the present invention, but is only referenced herein with respect to one potential embodiment of the present invention. The use of a diode and associated resistors with respect to an embodiment simply represents one possible "neuron" implementation. Such a configuration can be said to comprise an artificial neuron. It is anticipated that other devices and components

can be utilized instead of a diode to construct a physical neural network and a neuron-like node (i.e., artificial neuron), as indicated herein.

Thus, neuron 200 shown in Appellant's FIG. 2 comprises a neuron-like node that may include a diode 206, which is labeled $D_1$, and a resistor 204, which is labeled $R_2$. Resistor 204 is connected to a ground 210 and an input 205 of diode 206. Additionally, a resistor 202, which is represented as a block and labeled $R_1$, can be connected to input 205 of diode 206. Block 202 includes an input 212, which comprises an input to neuron 200. A resistor 208, which is labeled $R_3$, is also connected to an output 214 of diode 206. Additionally, resistor 208 is coupled to ground 210. Diode 206 in a physical neural network is analogous to a neuron of a human brain, while an associated connection formed thereof, as explained in greater detail herein, is analogous to a synapse of a human brain.

As depicted in FIG. 2, the output 214 is determined by the connection strength of $R_1$ (i.e., resistor 202). If the strength of $R_1$'s connection increases (i.e., the resistance decreases), then the output voltage at output 214 also increases. Because diode 206 conducts essentially no current until its threshold voltage (e.g., approximately .6V for silicon) is attained, the output voltage will remain at zero until $R_1$ conducts enough current to raise the pre-diode voltage to approximately .6V. After .6V has been achieved, the output voltage at output 214 will increase linearly. Simply adding extra diodes in series or utilizing different diode types may increase the threshold voltage.

An amplifier may also replace diode 206 so that the output voltage immediately saturates at a reference threshold voltage, thus resembling a step function. $R_3$ (i.e., resistor 208) functions generally as a bias for diode 206 (i.e., $D_1$) and should generally be about 10 times larger than resistor 204 (i.e., $R_2$). In the circuit configuration illustrated in FIG. 2, $R_1$ can actually be configured as a network of connections composed of many inter-connected conducting nanowires (i.e., see FIG. 3). As explained previously, such connections are analogous to the synapses of a human brain.

FIG. 3 illustrates a block diagram illustrating a system 300 that includes, but is not limited to, a network of nanoconnections 304 formed between two or more electrodes, in accordance with one embodiment of the present invention.

Nanoconnections 304 (e.g., nanoconductors) depicted in FIG. 3 can be located between input 302 and output 306. The network of nanoconnections depicted in FIG. 3 can be implemented as a network of molecules, including, for example, nanoconductors. Examples of nanoconductors include devices such as, for example, nanowires, nanotubes, and nanoparticles.

Nanoconnections 304, which are analogous to biological synapses, can be composed of electrical conducting material (i.e., nanoconductors). Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules. A nanoconductor can also be implemented as, for example, DNA. Studies have shown that DNA has special electrical properties which can function as essentially a tiny electrical wire. This recent discovery opens up a possible route to new applications in the electronics industry and particularly with respect to the physical neural network disclosed herein.

Carbon particles (e.g., granules or bearings) can also be utilized for developing nanoconnections. The nanoconductors utilized to form a connection network can be formed as a plurality of nanoparticles. For example, each nanoconnection within a connection network can be formed from a chain of carbon nanoparticles. Thus, nanoconductors that are utilized to form a physical neural network can be formed from such nanoparticles. Note that as utilized herein, the term "nanoparticle" can be utilized interchangeably with the term "nanoconductor." The term "nanoparticle" can refer simply to a particular type of nanoconductors, such as, for example, a carbon nanoparticle, or another type of nanoconductors, such as, for example, a carbon nanotube or carbon nanowire. Devices that conduct electricity and have dimensions on the order of nanometers can be referred to as nanoconductors.

Appellant's connection network can be composed from a variety of different types of nanoconductors. For example, a connection network can be formed from a plurality of nanoconductors, including nanowires, nanotubes and/or other types of nanoparticles or molecular conductors. Note that such nanowires, nanotubes and/or nanoparticles, along with other types of nanoconductors can be formed from

materials such as carbon or silicon. For example, carbon nanotubes may comprise a type of nanotube that can be utilized in accordance with the present invention.

As illustrated in FIG. 3, nanoconnections 304 comprise a plurality of interconnected nanoconnections, which can be referred to generally as a "connection network." An individual nanoconnection may constitute a nanoconductor such as, for example, a nanowire, a nanotube, nanoparticles(s), or any other nanoconducting structures. Nanoconnections 304 may comprise a plurality of interconnected nanotubes and/or a plurality of interconnected nanowires. Similarly, nanoconnections 304 can be formed from a plurality of interconnected nanoparticles.

A *connection network* is thus not one connection between two electrodes, but a plurality of connections between input electrodes and output electrodes. Nanotubes, nanowires, nanoparticles and/or other nanoconducting structures can be utilized, of course, to construct nanoconnections 304 between input 302 and input 306. Although a single input 302 and a single input 306 is depicted in FIG. 3, it can be appreciated that a plurality of inputs and a plurality of outputs can be implemented in accordance with the present invention, rather than simply a single input 302 or a single output 306.

FIG. 4 illustrates a block diagram illustrating a plurality of connections 414 between inputs 404, 406, 408, 410, 412 and outputs 416 and 418 of a physical neural network, in accordance with one embodiment of the present invention. Inputs 404, 406, 408, 410, and 412 provide input signals to connections 414. Output signals are then generated from connections 414 via outputs 416 and 418. A connection network can thus be configured from the plurality of connections 414. Such a connection network is generally associated with one or more neuron-like nodes.

The connection network also comprises a plurality of interconnected nanoconnections, wherein each nanoconnection thereof is strengthened or weakened according to an application of an electric field. A connection network is not possible if built in one layer because the presence of one connection can alter the electric field so that other connections between adjacent electrodes could not be formed. Instead, such a connection network can be built in layers, so that each

connection thereof can be formed without being influenced by field disturbances resulting from other connections. This can be seen in FIG. 5.

FIG. 5 illustrates a schematic diagram of a physical neural network 500 that can be created without disturbances, in accordance with one embodiment of the present invention. Physical neural network 500 is composed of a first layer 558 and a second layer 560. A plurality of inputs 502, 504, 506, 508, and 510 can be respectively provided to layers 558 and 560 respectively via a plurality of input lines 512, 514, 516, 518, and 520 and a plurality of input lines 522, 524, 526, 528, and 530. Input lines 512, 514, 516, 518, and 520 are further coupled to input lines 532, 534, 536, 538, and 540 such that each line 532, 534, 536, 538, and 540 is respectively coupled to nanoconnections 572, 574, 576, 578, and 580. Thus, input line 532 can be connected to nanoconnections 572. Input line 534 can be connected to nanoconnections 574, and input line 536 can be connected to nanoconnections 576. Similarly, input line 538 can be connected to nanoconnections 578, and input line 540 is generally connected to nanoconnections 580.

Nanoconnections 572, 574, 576, 578, and 580 may comprise nanoconductors such as, for example, nanotubes and/or nanowires. Nanoconnections 572, 574, 576, 578, and 580 thus comprise one or more nanoconductors. Additionally, input lines 522, 524, 526, 528, and 530 are respectively coupled to a plurality of input lines 542, 544, 546, 548 and 550, which are in turn each respectively coupled to nanoconnections 582, 584, 586, 588, and 590.

Thus, for example, input line 542 is connected to nanoconnections 582, while input line 544 is connected to nanoconnections 584. Similarly, input line 546 is connected to nanoconnections 586 and input line 548 is connected to nanoconnections 588. Additionally, input line 550 is connected to nanoconnections 590. Box 556 and 554 generally represent simply the output and are thus illustrated connected to outputs 562 and 568. In other words, outputs 556 and 554 respectively comprise outputs 562 and 568. The aforementioned input lines and associated components thereof actually comprise physical electronic components, including conducting input and output lines and physical nanoconnections, such as nanotubes and/or nanowires.

Thus, the number of layers 558 and 560 equals the number of desired outputs 562 and 568 from physical neural network 500. In the previous two figures, every input was potentially connected to every output, but many other configurations are possible. The connection network can be made of any electrically conducting material, although the practicality of the application requires that they be very small so that they will align with a practical voltage. Carbon nanotubes or any conductive nanowire can be implemented in accordance with Appellant's physical neural network. Such components can thus form connections between electrodes by the presence of an electric field.

The only general requirements for the conducting material utilized to configure the nanoconductors are that such conducting material must conduct electricity, and a dipole should preferably be induced in the material when in the presence of an electric field. Alternatively, the nanoconductors utilized in association with the physical neural network described herein can be configured to include a permanent dipole that is produced by a chemical means, rather than a dipole that is induced by an electric field. A connection network could also be configured from other conductive particles that are developed or found useful in the nanotechnology arts. For example, carbon particles (e.g., carbon "dust") may also be used as nanoconductors in place of nanowires or nanotubes. Such particles may include bearings or granule-like particles.

Appellant's connection network can be constructed as follows. Initially, a voltage can be applied across a gap that is filled with a mixture of nanowires and a "solvent". This mixture can be composed of a variety of materials or substances. The only general requirement in constructing such a connection network is that the conducting wires should be suspended in the solvent and/or dissolved or in a suspension, but free to move about. Additionally, the electrical conductance of the substance should generally be less than the electrical conductance of the suspended conducting nanowire(s) and/or other nanoparticle(s). The viscosity of the substance should not be too much so that the conducting nanowire(s) and/or other nanoparticles(s) cannot move when an electric field is applied.

The goal for such a connection network is to develop a network of connections of just the "right" values so as to satisfy particular signal-processing

requirements, which is precisely how a neural network functions. Applying a voltage across a space occupied by the aforementioned mixture can form a connection network. To create a connection network, input terminals can be selectively raised to a positive voltage, while the output terminals can be selectively grounded.

Alternatively, an electric field, either AC or DC, can be applied across the terminals. Such an electric field can be, for example, a sinusoidal, square or a saw-tooth waveform. Thus, connections can gradually form between the inputs and outputs. The important requirement that makes a physical neural network functional as a neural network in accordance with an embodiment of the present invention is that the longer this electric field is applied across the connection gap, and/or the greater the frequency or amplitude of the field, the more nanotubes and/or nanowires and/or nanoparticles align and the stronger the connections thereof become.

The connections can either be initially formed and possess random resistances or no connections may be formed at all. By initially forming random connections, it might be possible to teach the desired relationships faster, because it is not necessary for the base connections to be constructed from scratch. Depending on the rate of connection decay, having initial random connections could prove faster, although not necessarily. The connection network can adapt itself to the requirements of a given situation regardless of the initial state of the connections.

The resistance of a connection can be maintained or lowered by selective activations of the connection. In other words, an electric field can be applied perpendicular to the direction of connection formation by perpendicular electrodes. Alternately, both the input and output electrodes could be given the same sinusoidal, alternating signal, which would create pulses of electrostatic repulsion in the connection region. The temperature of the solution can also be controlled so that the rate that connection degradation can be controlled.

The nanoconnections may or may not be arranged in an orderly array pattern between the input and output electrodes. The nanoconnections (e.g., nanotubes,

nanowires, etc) of a physical neural network do not have to order themselves into neatly formed arrays. They simply float in the solution, or lie at the bottom of the gap, and more or less line up in the presence an electric field. Precise patterns are thus not necessary. In fact, neat and precise patterns may not be desired. Rather, precise patterns could be a drawback rather than an advantage. In fact, it may be desirable that the connections themselves function as poor conductors, so that variable connections are formed thereof, overcoming simply an "on" and "off" structure, which is commonly associated with binary and serial networks and structures thereof.

Although it can be seen that nanoparticles aligned in a dielectric medium (e.g., a dielectric solvent or dielectric solution) can offer a unique solution to emulated modifiable, variable connections within an electronic implementation of a neural network, it is not yet obvious how one would provide feedback that would train the connections. A training mechanism may be implemented in many different forms. Basically, the connections in a connection network must be able to change in accordance with the feedback provided. In other words, the very general notion of connections being strengthened or connections being weakened in a *physical* system is the essence of Appellant's described physical neural network.

Thus, it can be appreciated that the training of such a physical neural network may not require a "CPU" to calculate connection values thereof. Appellant's physical neural network, including artificial synapses thereof, can adapt itself. Complicated neural network solutions could be implemented very rapidly "on the fly", much like a human brain adapts as it performs. It is anticipated that various learning mechanisms can be implemented in accordance with preferred or alternative embodiments of the present invention. Two such learning mechanisms are generally discussed herein. First, a feedback mechanism is described that leads to the training of a multi-layer, feed-forward network. Second, a feedback mechanism is generally discussed, which can result in Hebbian synapse modification within recurrent, highly interconnected networks.

The physical neural network disclosed in Appellant's specification thus has a number of broad applications. The core concept of such a physical neural network, however, is basic. The very basic idea that the connection values between electrode junctions by nanoconductors can be used in a neural network devise is all that required to develop an enormous number of possible configurations and applications thereof.

An important feature of a physical neural network is the ability to form negative connections. This is an important feature that makes possible inhibitory effects useful in data processing. The basic idea is that the presence of one input can inhibit the effect of another input. In artificial neural networks as they currently exist, this is accomplished by multiplying the input by a negative connection value. Unfortunately, with a physical device, the connection may only take on zero or positive values under such a scenario

In other words, either there can be a connection or no connection. A connection can simulate a negative connection by dedicating a particular connection to be negative, but one connection cannot begin positive and through a learning process change to a negative connection. In general, if it starts positive, it can only go to zero. In essence, it is the idea of possessing a negative connection initially that results in the simulation, because this does not occur in a biological network. Only one type of signal travels through axons and dendrites in a biological network. That signal is transferred into the flow of a neurotransmitter whose effect on the receiving neuron can be either excitatory or inhibitory, depending on the neuron, thereby dedicating certain connections inhibitory and excitatory

One method for solving this problem is to utilize two sets of connections for the same output, having one set represent the positive connections and the other set represent the negative connections. The output of these two layers can be compared, and the layer with the greater output will output either a high signal or a low signal, depending on the type of connection set (inhibitory or excitatory). Such a configuration be seen in FIG. 5, where the excitatory output can be, for example, a layer 1 output and the inhibitory output can be a layer 2 output.

A truth table for the output of circuit 700 is illustrated at block 780 in FIG. 7. As indicated at block 780, when an excitatory output is high and the inhibitory output is also high, the final output is low. When the excitatory output is high and the inhibitory output is low, the final output is high. Similarly, when the excitatory output is low and the inhibitory output is high, the final output is low. When the excitatory output is low and the inhibitory output is also low, the final output is low. Note that layers 704 and 708 may thus comprise excitatory connections, while layers 706 and 710 may comprise inhibitory connections.

At all times during the learning process, a weak alternating electric field can be applied perpendicular to the connections. This can cause the connections to weaken by rotating the nanotube perpendicular to the connection direction. This weakening of connections is important because it can allow for a much higher degree of adaptation. To understand this, one must realize that the connections cannot (practically) keep getting stronger and stronger. By weakening those connections not contributing much to the desired output, we decrease the necessary strength of the needed connections and allow for more flexibility in continuous training. Other mechanisms, such as increasing the temperature of the nanotube suspension could also be used for such a purpose.

The circuit depicted in FIG. 7 can be separated into two separate circuits. The first part of the circuit can be composed of nanotube connections, while the second part of the circuit comprises the "neurons" and the learning mechanism (i.e., op-amps/comparator). The learning mechanism on first glance appears similar to a relatively standard circuit that could be implemented on silicon with current technology. Such a silicon implementation can thus comprise the "neuron" portion of the chip.

The second part of the circuit (i.e., the connections) is thus a new type of chip structure, although it could be constructed with current technology. The connection chip can be composed of an orderly array of electrodes spaced anywhere from, for example, 100nm to 1μm or perhaps even further. In a biological system, one talks of synapses connecting neurons. It is in the synapses where the

information is processed, (i.e., the "connection weights"). Similarly, such a chip can contain all of the synapses for the physical neural network. A possible 2-diminsional arrangement thereof can be seen in FIG. 8.

The training of such a chip is primarily based on two assumptions. First, the inherent parallelism of a physical neural network or system can permit all training sessions to occur simultaneously, no matter how large the associated connection network. Second, recent research has indicated that near perfect aligning of nanotubes can be accomplished in no more than 15 minutes utilizing practical voltages of about 5V.

If one considers that the input data, arranged as a vector of binary "high's" and "low's" is presented to the network or system simultaneously, and that all training vectors are presented one after the other in rapid succession (e.g., perhaps 100 MHz or more), then each connection would "see" a different frequency in direct proportion to the amount of time that its connection is required for accurate data processing (i.e., provided by a feedback mechanism). Thus, if it only takes approximately 15 minutes to attain an almost perfect state of alignment, then this amount of time would comprise the longest amount of time required to train, assuming that all of the training vectors are presented during that particular time period and adequate feedback has been provided.

FIG. 9 illustrates a flow chart 900 of logical operational steps that can be followed to construct a connection network, in accordance with an embodiment of the present invention. Initially, as indicated at block 902, a connection gap is created from a connection network structures. As indicated earlier, the goal for such a connection network is generally to develop a network of connections of "just" the right values to satisfy particular information processing requirements, which is precisely what a neural network accomplishes. As illustrated at block 904, a solution is prepared, which is composed of nanoconductors and a "solvent." Note that the term "solvent" as utilized herein has a variable meaning, which includes the traditional meaning of a "solvent," and also a suspension.

The solvent utilized can comprise a volatile liquid that can be confined or sealed and not exposed to air. For example, the solvent and the nanoconductors present within the resulting solution can be sandwiched between wafers of silicon or other materials. If the fluid has a melting point that is approximately at operating temperature, then the viscosity of the fluid could be controlled easily. Thus, if it is desired to lock the connection values into a particular state, the associated physical neural network can be cooled slightly until the fluid freezes. The term "solvent" as utilized herein thus can include fluids such as for example, toluene, hexadecane, mineral oil, liquid crystals, etc. Note that the solution in which the nanoconductors (i.e., nanoconnections) are present should generally comprise a substance that does not conduct electricity and allows for the suspension of nanoparticles.

Thus, when the resistance between the electrodes is measured, the conductivity of the nanoconductors can be measured, not that of the solvent. The nanoconductors can be suspended in the solution or can alternately lie on the bottom surface of the connection gap if the gap is 2-diminsional (i.e., formed on a planar surface such as electrodes deposited on the surface of a substrate). Note that the solvent and/or solutions described herein may also comprise liquid crystal media.

As illustrated thereafter at block 906, the nanoconductors must be suspended in the solvent, either dissolved or in a suspension of sorts, but generally free to move around, either in the solution or on the bottom surface of the gap. As depicted next at block 908, the electrical conductance of the solution must be less than the electrical conductance of the suspended nanoconductor(s). Next, as illustrated at block 910, the viscosity of the substance should not be too much so that the nanoconductors cannot move when an electric field (e.g., voltage) is applied across the electrodes. Finally, as depicted at block 912, the resulting solution of the "solvent" and the nanoconductors is thus located within the connection gap.

Note that although a logical series of steps is illustrated in FIG. 9, it can be appreciated that the particular flow of steps can be re-arranged. Thus, for example,

the creation of the connection gap, as illustrated at block 902, may occur after the preparation of the solution of the solvent and nanoconductor(s), as indicated at block 904. FIG. 9 thus represents merely possible series of steps, which can be followed to create a connection network. It is anticipated that a variety of other steps can be followed as long as the goal of achieving a connection network in accordance with the present invention is achieved. Similar reasoning also applies to FIG. 10.

FIG. 10 illustrates a flow chart 1000 of logical operations steps that can be followed to strengthen nanoconductors within a connection gap, in accordance with a preferred of the present invention. As indicated at block 1002, an electric field can be applied across the connection gap discussed above with respect to FIG. 9. The connection gap can be occupied by the solution discussed above. As indicated thereafter at block 1004, to create the connection network, the input terminals can be selectively raised to a positive voltage while the output terminals are selectively grounded.

As illustrated thereafter at block 1006, connections thus form between the inputs and the outputs. The important requirements that make the resulting physical neural network functional as a neural network is that the longer this electric field is applied across the connection gap, or the greater the frequency or amplitude, the more nanoconductors align and the stronger the connection becomes. Thus, the connections that experience the most feedback during training become the strongest.

As indicated at block 1008, the connections can either be initially formed and have random resistances or no connections will be formed at all. By forming initial random connections, it might be possible to teach the desired relationships faster, because the base connections do not have to be built up as much. Depending on the rate of connection decay, having initial random connections could prove to be a faster method, although not necessarily. A connection network will adapt itself to whatever is required regardless of the initial state of the connections.

Thus, as indicated at block 1010, as the electric field is applied across the connection gap, the more the nonconductor(s) will align and the stronger the connection becomes. Connections (i.e., synapses) that are not used are dissolved back into the solution, as illustrated at block 1012. As illustrated at block 1014, the resistance of the connection can be maintained or lowered by selective activations of the connections. In other words, "if you do not use the connection, it will fade away," much like the connections between neurons in a human brain in response to Long Term Depression, or LTD.

The neurons in a human brain, although seemingly simple when viewed individually, interact in a complicated network that computes with both space and time. The most basic picture of a neuron, which is usually implemented in technology, is a summing device that adds up a signal. Actually, this statement can be made even more general by stating that a neuron adds up a signal in discrete units of time. In other words, every group of signals incident upon the neuron can be viewed as occurring in one moment in time. Summation thus occurs in a spatial manner. The only difference between one signal and another signal depends on where such signals originate. Unfortunately, this type of data processing excludes a large range of dynamic, varying situations that cannot necessarily be broken up into discrete units of time.

The example of speech recognition is a case in point. Speech occurs in the time domain. A word is understood as the temporal pronunciation of various phonemes. A sentence is composed of the temporal separation of varying words. Thoughts are composed of the temporal separation of varying sentences. Thus, for an individual to understand a spoken language at all, a phoneme, word, sentence or thought must exert some type of influence on another phoneme, word, sentence or thought. The most natural way that one sentence can exert any influence on another sentence, in the light of neural networks, is by a form of temporal summation. That is, a neuron "remembers" the signals it received in the past.

The human brain can accomplish such a feat in an almost trivial manner. When a signal reaches a neuron, the neuron has an influx of ions rush through its

membrane. The influx of ions contributes to an overall increase in the electrical potential of the neuron. Activation is achieved when the potential inside the cell reaches a certain threshold. The one caveat is that it takes time for the cell to pump out the ions, something that it does at a more or less constant rate. So, if another signal arrives before the neuron has time to pump out all of the ions, the second signal will add with the remnants of the first signal and achieve a raised potential greater than that which could have occurred with only the second signal. The first signal influences the second signal, which results in temporal summation.

Implementing this in a technological manner has proved difficult in the past. Any simulation would have to include a "memory" for the neuron. In a digital representation, this requires data to be stored for every neuron, and this memory would have to be accessed continually. In a computer simulation, one must discritize the incoming data, since operations (such as summations and learning) occur serially. That is, a computer can only do one thing at a time. Transformations of a signal from the time domain into the spatial domain require that time be broken up into discrete lengths, something that is not necessarily possible with real-time analog signals in which no point exists within a time-varying signal that is uninfluenced by another point.

A physical neural network, however, is generally not digital. A physical neural network is a massively parallel analog device. The fact that actual molecules (e.g., nanoconductors) must move around (in time) makes one form of temporal summation a natural occurrence. This temporal summation is built into the nanoconnections and can occur at a time scale much longer that that which is possible with capacitors and standard analog circuitry in micron dimension VLSI designs. The easiest way to understand this is to view the multiplicity of nanoconnections as one connection with one input into a neuron-like node (Op-amp, Comparator, etc.). This can be seen in Appellant's FIG. 11.

FIG. 11 illustrates a schematic diagram of a circuit 1100 demonstrating temporal summation within a neuron, in accordance with one embodiment of the present invention. As indicated in FIG. 11, an input 1102 can be provided to

nanoconnections 1104, which in turn provides a signal, which can be input to an amplifier 1110 (e.g., op amp) at node B. A resistor 1106 can be connected to node A, which in turn is electrically equivalent to node B. Node B can be connected to a negative input of amplifier 1100. Resistor 1108 can also be connected to a ground 1108. Amplifier 1110 can provide output 1114. Note that although nanoconnections 1104 is referred to in the plural it can be appreciated that nanoconnections 1104 can comprise a single nanoconnection or a plurality of nanoconnections. For simplicity sake, however, the plural form is used to refer to nanoconnections 1104.

Input 1102 can be provided by another physical neural network or system to cause increased connection strength of nanoconnections 1104 over time. This input will most likely arrive in pulses, but can also be continuous, depending upon a desired implementation. A constant or pulsed electric field perpendicular to the connections would serve to constantly erode the connections, so that only signals of a desired length or amplitude could cause a connection to form.

Once the connection is formed, the voltage divider formed by nanoconnection 1104 and resistor 1106 can cause a voltage at node A in direct proportion to the strength of nanoconnections 1104. When the voltage at node A reaches a desired threshold, the amplifier (i.e., an op-amp and/or comparator), will output a high voltage (i.e., output 1114). The key to the temporal summation is that, just like a real neuron, it takes time for the electric field to breakdown the nanoconnections 1104, so that signals arriving close in time will contribute to the firing of the neuron (i.e., op-amp, comparator, and forth). Temporal summation has thus been achieved. The parameters of the temporal summation could be adjusted by the amplitude and frequency of the input signals and the perpendicular electric field.

FIG. 12 illustrates a block diagram illustrating a pattern recognition system 1200, which can be implemented with a physical neural network device 1222, in accordance with an alternative embodiment of the present invention. Note that the pattern recognition system 1200 can be implemented as a speech recognition system. Although a pattern recognition system 1200 is depicted herein in the

context of speech recognition, a physical neural network device (can be implemented in association with other types of pattern recognition systems, such as visual and/or imaging recognition systems.

FIG. 12 thus is not considered a limiting feature of the present invention but is presented for general edification and illustrative purposes only. The diagram depicted in FIG. 12 can, of course, be modified as new applications and hardware are developed. The development or use of a pattern recognition system such as pattern recognition system 1200 of FIG. 12 by no means limits the scope of the physical neural network disclosed in Appellant's specification.

FIG. 12 illustrates in block diagram fashion, a system structure of a speech recognition device using a neural network according to one alternative embodiment of the present invention. The pattern recognition system 1200 depicted in FIG. 12 can be provided with a CPU 1211 (e.g., a microprocessor) for performing the functions of inputting vector rows and instructor signals (vector rows) to an output layer for the learning process of a physical neural network device 1222, and changing connection weights between respective neuron devices based on the learning process. Pattern recognition system 1200 can be implemented within the context of a data-processing system, such as, for example, a personal computer or personal digital assistant (PDA), both of which are well known in the art.

The CPU 1211 can perform various processing and controlling functions, such as pattern recognition, including but not limited to speech and/or visual recognition based on the output signals from the physical neural network device 1222. The CPU 1211 is connected to a read-only memory (ROM) 1213, a random-access memory (RAM) 1214, a communication control unit 1215, a printer 1216, a display unit 1217, a keyboard 1218, an FFT (fast Fourier transform) unit 1221, a physical neural network device 1222 and a graphic reading unit 1224 through a bus line 1220 such as a data bus line. The bus line 1220 may comprise, for example, an ISA, EISA, or PCI bus.

The ROM 1213 is a read-only memory storing various programs or data used by the CPU 1211 for performing processing or controlling the learning process, and

speech recognition of the physical neural network device 1222. The ROM 1213 may store programs for carrying out the learning process according to error back-propagation for the physical neural network device or code rows concerning, for example, 80 kinds of phonemes for performing speech recognition. The code rows concerning the phonemes can be utilized as second instructor signals and for recognizing phonemes from output signals of the neuron device network. Also, the ROM 1213 can store programs of a transformation system for recognizing speech from recognized phonemes and transforming the recognized speech into a writing (i.e., written form) represented by characters.

A predetermined program stored in the ROM 1213 can be downloaded and stored in the RAM 1214. RAM 1214 generally functions as a random access memory used as a working memory of the CPU 1211. In the RAM 1214, a vector row storing area can be provided for temporarily storing a power obtained at each point in time for each frequency of the speech signal analyzed by the FFT unit 1221. A value of the power for each frequency serves as a vector row input to a first input portion of the physical neural network device 1222. Further, in the case where characters or graphics are recognized in the physical neural network device, the image data read by the graphic reading unit 1224 are stored in the RAM 1214.

The communication control unit 1215 transmits and/or receives various data such as recognized speech data to and/or from another communication control unit through a communication network 1202 such as a telephone line network, an ISDN line, a LAN, or a personal computer communication network. Network 1202 may also comprise, for example, a telecommunications network, such as a wireless communications network. Communication hardware methods and systems thereof are well known in the art.

The printer 1216 can be provided with a laser printer, a bubble-type printer, a dot matrix printer, or the like, and prints contents of input data or the recognized speech. The display unit 1217 includes an image display portion such as a CRT display or a liquid crystal display, and a display control portion. The display unit 1217 can display the contents of the input data or the recognized speech as well as

a direction of an operation required for speech recognition utilizing a graphical user interface (GUI).

The keyboard 1218 generally functions as an input unit for varying operating parameters or inputting setting conditions of the FFT unit 1221, or for inputting sentences. The keyboard 1218 is generally provided with a ten-key numeric pad for inputting numerical figures, character keys for inputting characters, and function keys for performing various functions. A mouse 1219 can be connected to the keyboard 1218 and serves as a pointing device.

A speech input unit 1223, such as a microphone can be connected to the FFT unit 1221. The FFT unit 1221 transforms analog speech data input from the voice input unit 1223 into digital data and carries out spectral analysis of the digital data by discrete Fourier transformation. By performing a spectral analysis using the FFT unit 1221, the vector row based on the powers of the respective frequencies are output at predetermined intervals of time. The FFT unit 1221 performs an analysis of time-series vector rows, which represent characteristics of the inputted speech. The vector rows output by the FFT 1221 are stored in the vector row storing area in the RAM 1214.

The graphic reading unit 224, provided with devices such as a CCD (Charged Coupled Device), can be used for reading images such as characters or graphics recorded on paper or the like. The image data read by the image-reading unit 1224 are stored in the RAM 1214.

The implications of a physical neural network are tremendous. With existing lithography technology, many electrodes in an array such as depicted in FIG. 5 or 14 can be etched onto a wafer of silicon. The "neurons" (i.e., amplifiers, diodes, etc.), as well as the training circuitry illustrated in FIG. 6, could be built onto the same silicon wafer. By building the neuron circuitry on one side of a substrate, and the electrode arrays on the other side, chips can be built that are no longer limited in synapse density. A solution of suspended nanoconductors could be placed between the electrode connections and the chip could be packaged. One could also place a rather large network parallel with a computer processor as part of a larger

system. Such a network, or group of networks, can add significant computational capabilities to standard computers and associated interfaces.

For example, such a chip can be constructed utilizing a standard computer processor in parallel with a large physical neural network or group of physical neural networks. A program can then be written such that the standard computer teaches the neural network to read, or create an association between words, which is precisely the same sort of task in which neural networks can be implemented. This would amount to nothing more than presenting the network with a pre-defined sequence of input and output patterns stored in memory.

Once the physical neural network is able to "read", it can be taught for example to "surf" the Internet and find material of any particular nature. A search engine can then be developed that does not search the Internet by "keywords", but instead by meaning. This idea of an intelligent search engine has already been proposed for standard neural networks, but until now has been impractical because the network required was too big for a standard computer to simulate. The use of a physical neural network as disclosed herein now makes a truly intelligent search engine possible.

A physical neural network can be utilized in other applications, such as, for example, speech recognition and synthesis, visual and image identification, management of distributed systems, self-driving cars and filtering. Such applications have to some extent already been accomplished with standard neural networks, but are generally limited in expense, practicality and not very adaptable once implemented.

The use of a physical neural network can permit such applications to become more powerful and adaptable. Indeed, anything that requires a bit more "intelligence" could incorporate a physical neural network. One of the primary advantages of a physical neural network is that such a device and applications thereof can be very inexpensive to manufacture, even with present technology. The lithographic techniques required for fabricating the electrodes and channels there between has already been perfected and implemented in industry.

Most problems in which a neural network solution is generally implemented are complex adaptive problems, which change in time. An example is weather prediction. The usefulness of a physical neural network is that it could handle the enormous network needed for such computations and adapt itself in real-time.

The training of multiple connection networks between neuron layers within a multi-layer neural network is an important feature of any neural network. The addition of neuron layers to a neural network can increase the ability of the network to create increasingly complex associations between inputs and outputs. Unfortunately, the addition of extra neuron layers in a network raises an important question: How does one optimize the connections within the hidden layers to produce the desired output?

The neural network field was stalled for some time trying to answer this question until several parties simultaneously stumbled onto a computationally efficient solution, now referred to generally as "back-propagation" or "back-prop" for short. As the name implies, the solution involves a propagation of error *back* from the output to the input. Essentially, back-propagation amounts to efficiently determining the minimum of an error surface composed of *n* variables, where the variable *n* represents the number of connections.

Because back propagation is a computational algorithm, this concept may not make much sense *physically*. Another related question to ask is can the neurons in a human brain take a derivative? Do they "know" the result of a connection on another neuron? In other words, how does a neuron *know* what the desired output is if each neuron is an independent summing machine, only concerned with its own activation level and firing only when that activation is above threshold? What exactly can a neuron "know" about its environment?

Although this question is certainly open for debate, it is plausible to state that a neuron can only "know" if it has fired and whether or not its own connections have caused the firing of other neurons. This is precisely the Hebbian hypothesis for learning: "if neuron A repeatedly takes part in firing neuron B, then the connection between neuron A and B strengthens so that neuron A can more

efficiently take part in firing neuron B". With this hypothesis, a technique can be derived to train a multi-layer physical neural network device without utilizing back-propagation or any other training "algorithm", although the technique mirrors back-propagation in form, as information is transferred from output layers to input layers, providing feedback in the form of pulses that modify connections.

In fact, the resulting physical neural network can be self-adaptable and does not require any calculations. In other words, the network and its training mechanism can be a physical process that arises from feedback signals within the network. The structure of the physical neural network or synapse thereof thus creates a situation in which learning simply takes place when a desired output is given. The description that follows is thus based on the use of a physical neural network and constituent nanoconnections thereof.

FIG. 13 illustrates a schematic diagram of a 2-input, 1-output, 2-layer inhibitory physical neural network 1300, which can be implemented in accordance with one embodiment of the present invention. As indicated in FIG. 13, two layers 1326 and 1356 of physical neural network 1300 can be distinguished from one another. Note that as utilized herein, the term "layer" can be defined as comprising a connection network. Such a connection network can include one or more neurons in association with a plurality of nanoconductors present in a solvent, as explained herein. In FIG. 13, layers 1326 and 1356 are respectively labeled L1 and L2. Inputs 1304 and 1306 to a connection network 1302 are also indicated in FIG. 13, wherein inputs 1304 and 1306 are respectively labeled I1 and I2 and connection network 1302 is labeled C1.

Inputs 1304 and 1302 (i.e. I1 and I2) generally provide one or more signals, which can be propagated through connection network 1302 (i.e., C1). Connection network 1302 thus generates a first output signal at node 1303 and a second output signal at node 1305. The first output signal provided at node 1303 is further coupled to an input 1323 of an amplifier 1312, while the signal output signal provided at node 1305 is connected to an input 1325 of an amplifier 1314. Amplifier 1312 thus includes two inputs 1323 and 1311, while amplifier 1314

includes two inputs 1315 and 1325. Note that a voltage $V_t$ can be measured at input 1311 to amplifier 1312. Similarly, voltage $V_t$ can also be measured at input 1315 to amplifier 1314. Additionally, a resistor 1316 can be coupled to node 1305 and a resistor 1310 is connected to node 1303. Resistor 1310 is further coupled to a ground 1309. Resistor 1316 is further connected to ground 1309. Resistors 1310 and 1316 are labeled $R_b$ in FIG. 13.

Amplifier 1312 can thus function as a neuron A and amplifier 1314 functions as a neuron B. The two neurons, A and B, respectively sum the signals provided at nodes 1303 and 1305 to provide output signals thereof at nodes 1319 and 1321 (i.e., respectively H1 and H2). Additionally, a switch 1308, which is labeled S1, is connected between nodes 1303 and 1319. Likewise, a switch 1322, which is also labeled S1, is connected between nodes 1305 and 1321. A resistor 1318 is coupled between an output of amplifier 1312 and node 1319. Similarly, a resistor 1320 is coupled between an output of amplifier 1314 and node 1321. Node 1319, which carries signal H1, is connected to a connection network 1328. Also, node 1321, which carries signal H2, is connected to connection network 1328.

Note that connection network 1328 is labeled C2 in FIG. 3. A first signal can be output from connection network 1328 at node 1331. Likewise, a second signal can be output from connection network 1328 at node 1333. A resistor 1330, which is labeled $R_b$, is coupled between node 1331 and ground 1309. Also, a resistor 1334, which is also labeled $R_b$, is connected between node 1333 and ground 1309. Node 1333 is further connected to an input 1353 to amplifier 1338, while node 1331 is further coupled to an input 1351 to amplifier 1336. Note that resistor 1330 is also coupled to input 1351 at node 1331, while resistor 1334 is connected to input 1353 at node 1333.

A voltage $V_t$ can be measured at an input 1335 to amplifier 1336 and an input 1337 to amplifier 1338. Amplifiers 1335 and 1338 can be respectively referred to as neurons C and D. An output from amplifier 1336 is connected to a NOT gate 1340, which provides a signal that is input to a NOR gate 1342. Additionally, amplifier 1338 provides a signal, which can be input to NOR gate 1342.

Such a signal, which is output from amplifier 1338 can form an inhibitory signal, which is input to NOR gate 1342. Similarly, the output from amplifier 1336 can comprise an excitatory signal, which is generally input to NOT gate 1340. The excitatory and inhibitory signals respectively output from amplifiers 1336 and 1338 form an excitatory/inhibitory signal pair. NOR gate 1342 generates an output, which is input to an amplifier 1344 at input node 1347. A voltage $V_d$ can be measured at input node 1346, which is coupled to amplifier 1344.

Thus, the signals H1 and H2, which are respectively carried at nodes 1319 and 1321, are generally propagated through connection network 1328, which is labeled C2, where the signals are again summed by the two neurons, C and D (i.e., amplifiers 1336 and 1338). The output of these two neurons therefore form an excitatory/inhibitory signal pair, which through the NOT gate 1340 and the NOR gate 1342 are transformed into a signal output O1 as indicated at output 1348. Note that signal output node O1 can be measured at input node 1347 of amplifier 1344. Amplifier 1344 also includes an output node 1349, which is coupled to node 1331 through a switch 1350, which is labeled S2. Output 1349 is further coupled to a NOT gate 1354, which in turn provides an output which is coupled to node 133 through a switch 1352, which is also labeled S2.

For inhibitory effects to occur, it may be necessary to implement twice as many outputs from the final connection network as actual outputs. Thus, every actual output represents a competition between a dedicated excitatory signal and inhibitory signal. The resistors labeled $R_b$ (i.e., resistors 1330 and 1334) are generally very large, about 10 or 20 times as large as a nanoconnection. On the other hand, the resistors labeled $R_f$ (i.e., resistors 1318 and 1320) may possess resistance values that are generally less than that of a nanoconnection, although such resistances can be altered to affect the overall behavior of the associated physical neural network. $V_t$ represents the threshold voltage of the neuron while $V_d$ represents the desired output. S1 and S2 are switches involved in the training of layers 1 and 2 respectively (i.e., L1 and L2, which are indicated respectively by brackets 1326 and 1356 in FIG. 13).

For reasons that will become clear later, a typical training cycle can be described as follows. Initially, an input vector can be presented at I1 and I2. For this particular example, such an input vector generally corresponds to only 4 possible combinations, 11, 10, 01 or 00. Actual applications would obviously require many more inputs, perhaps several thousand or more. One should be aware that the input vector does not have to occur in discrete time intervals, but can occur in real time. The inputs also need not necessarily be digital, but for the sake of simplicity in explaining this example, digital representations are helpful. While an input pattern is being presented, a corresponding output can be presented at $V_d$. Again, in this particular case there is only one output with only two corresponding possible outcomes, 1 or 0. The desired output also does not have to be presented in discrete units of time.

For learning to occur, the switches 1350 and 1352 (i.e., S2) can be closed, followed by switches 1308 and 1322 (i.e., S1). Both groupings of switches (S1 and S2) can then be opened and the cycle thereof repeated. Although only two layers L1 and L2 are illustrated in FIG. 13, it can be appreciated that a particular embodiment of the present invention can be configured to include many more layers. Thus, if more than two layers exist, then the switches associated with the preceding layer can be initially closed, then the second to last, the third to last and so on, until the last switch is closed on the input layer. The cycle is repeated. This "training wave" of closing switches can occur at a frequency determined by the user. Although it will be explained in detail later, the more rapid the frequency of such a training wave, the faster the learning capabilities of the physical neural network.

For example, it can be assumed that no connections have formed within connection networks C1 or C2 and that inputs are being matched by desired outputs while the training wave is present. Since no connections are present, the voltage at neurons A, B, C and D are all zero and consequently all neurons output zero. One can quickly realize that whether the training wave is present or not, a voltage drop will not ensue across any connections other than those associated with the input connection network. The inputs, however, are being activated. Thus,

each input is seeing a different frequency. Connections then form in connection network C1, with the value of the connections essentially being random.

Before a connection has been made, the voltage incident on neurons A and B is zero, but after a connection has formed, the voltage jumps to approximately two diode drops short of the input voltage. This is because the connections form a voltage divider with $R_b$, such that $R_b$ (i.e., resistors 1310 and/or 1316) possesses a resistance very much larger than that of the nanoconnections. Two reasons for utilizing a large $R_b$ are to minimize power consumption of the physical neural network during a normal operation thereof, and to lower the voltage drop across the connections so that learning (i.e. connection modification) only takes place when feedback is present. Fortunately, nanotube contact resistances are on the order of about 100 kΩ, or more, which can allow for an $R_b$ of a few MΩ or greater. $V_t$ must be somewhere between two diode drops of the input voltage and the voltage produce by one nanoconnection in a voltage divider with $R_b$, the later being lower than the former.

Once connections have formed across C1 and grown sufficiently strong enough to activate neurons A and B, the connections across C2 can form in the same manner. Before continuing, however, it is important to determine what will occur to the nanoconnections of connection network 1302 (i.e., C1) after they grow strong enough to activate the first layer neurons. For the sake of example, assume that neuron A has been activated. When S1 is closed in the training wave, neuron A "sees" a feedback that is positive (i.e., activated). This locks the neuron into a state of activation, while S1 is closed. Because of the presence of diodes in connection network 1302 (i.e., C1), current can only flow from left to right in C1. This results in the lack of a voltage drop across the nanoconnections.

If another electric field is applied at this time to weaken the nanoconnections (e.g., perhaps a perpendicular field), the nanoconnections causing activation to the neuron can be weakened (i.e., the connections running from positive inputs to the neuron are weakened) This can also be accomplished by an increased temperature, which could naturally arise from heat dissipation of the other circuitry on the chip.

This feedback will continue as long as the connections are strong enough to activate the neuron (i.e., and no connections have formed in the second layer). Nanoconnections can thus form and be maintained at or near the values of neuron activation. This process will also occur for ensuing layers until an actual network output is achieved.

Although the following explanation for the training of the newly formed (and random) connections may appear unusual with respect to FIG. 13, the configuration depicted in FIG. 13 represents the smallest, simplest network available to demonstrate multi-layer training. A typical physical neural network can actually employ many more inputs, outputs and neurons. In the process of explaining training, reference is made to FIG. 13; however, embodiments of the present invention can be implemented with more than simply two inputs and one output.

FIG. 13 is thus described for illustrative purposes only and the number of inputs, outputs, neurons, layers, and so forth, should not be considered a limiting feature of the present invention, which is contemplated to cover physical neural networks that are implemented with hundreds, thousands, and even millions of such inputs, outputs, neurons, layers, and so forth. Thus, the general principles explained here with respect to FIG. 13 can be applied to physical neural networks of any size.

It can be appreciated from FIG. 13 that neuron C (i.e., amplifier 1336) is generally excitatory and neuron D (i.e., amplifier 1338) is generally inhibitory. The use of NOT gates 1340 and 1354 and NOR gate 1342 create a situation in which the output is only positive if neuron C is high and neuron D zero (i.e., only if the excitatory neuron C is high and the inhibitory neuron D low). For the particular example described herein with respect to FIG. 13, where only one output is utilized, there generally exists a fifty-fifty chance that the output will be correct.

Recall, however, that in a typical physical neural network many more outputs are likely to be utilized. If the output is high when the desired output is low, then the training neuron (i.e., amplifier 1344, the last neuron on the right in FIG. 13) outputs a high signal. When S2 is closed during the training wave, this means that

the post connections of the excitatory neuron will receive a high signal and the post connections of the inhibitory neuron a negative signal (i.e., because of the presence of NOT gate 1354). Note that through feedback thereof, each neuron will be locked into each state while S2 is closed.

Because of the presence of diodes within connection network 1328 (i.e., C2), there will be no voltage drop across those connections going to the excitatory neuron. There will be a voltage drop, however, across the nanoconnections extending from positive inputs of C2 to the inhibitory neuron (i.e., amplifier 1338). This can result in increases in inhibitory nanoconnections and a decrease in excitatory nanoconnections thereof (i.e., if an eroding is present). This is exactly what is desired if the desired output is low when the actual output is high. A correspondingly opposite mechanism strengthens excitatory connections and weakens inhibitory connections if the desired output is high when the actual output is low. When the desired output matches the actual output, the training neurons output is dependent on the gain of the differential amplifier.

Thus far an explanation has been presented describing how the last layer of a physical neural network can in essence train itself to match the desired output. An important concept to realize, however, is that the activations coming from the previous layer are basically random. Thus, the last connection network tries to match essentially random activations with desired outputs. For reasons previously explained, the activations emanating from the previous layer do not remain the same, but fluctuate. There must then be some way to "tell" the layers preceding the output layer which particular outputs are required so that their activations are no longer random.

One must realize that neurons simply cannot fire unless a neuron in a preceding layer has fired. The activation of output neurons can be seen as being aided by the activations of neurons in previous layers. An output neuron "doesn't care" what neuron in the previous layer is activating it, so long as it is able to produce the desired output. If an output neuron must produce a high output, then there must be at least one neuron in the previous layer that both has a connection

to it and is also activated, with the nanoconnection(s) being strong enough to allow for activation, either by itself or in combination with other activated neurons.

With this in mind, one can appreciate that the nanoconnections associated with pre-output layers can be modified. Again, by referring to FIG. 13, it can be appreciated that when S2 is closed (and S1 still open), $R_f$ may form a voltage divider with the connections of C2, with $R_b$ taken out of the picture. Recall that $R_f$ represents resistors 1318 and/or 1320, while $R_b$ represents resistors 1310 and/or 1316. Because of the diodes on every input and output of C2, only connections that go from a positive activation of neurons A and B to ground after C2 will allow current to flow. Recall as explained previously that only those nanoconnections that are required to be strengthened in the output connection matrix thereof will be negative, so that the voltage signals H1 and H2 measured respectively at nodes 1319 and 1321 are the direct result of how many neurons "need" to be activated in the output layer. In other words, the more neurons in layer i+1 that need activation, the lower the total equivalent resistance of all connections connecting a neuron in layer "i" and the neurons in layer "i+1" needing activation.

By thereafter closing S1, the previous layer neurons in essence "know" how much of their activation signal is being utilized. If their signal is being utilized by many neurons in a preceding layer, or by only a few with very strong nanoconnections, then the voltage that the neuron receives as feedback when S1 is closed decreases to a point below the threshold of the neuron. Exactly what point this occurs at is dependent on the value of $R_f$ (i.e., resistors 1318 and/or 1320) As $R_f$ becomes larger, less resistance is generally required to lower H1 or H2 to a point below the threshold of the neuron. This feedback voltage is very important, as this is how the network matches inputs with desired outputs. First, note that the feedback is local, confined to individual neurons. In essence, if a neuron needs to supply activations to many neurons, then it must strengthen its connections to neurons that are activating it, so that it may continue to do its job.

Several subtleties exist in this feedback process. Although the feedback voltage is largely determined by the neurons' pre-synaptic connections, (i.e.,

"axonal" connections), it is also determined by the neurons' post synaptic connections (i.e., dendritic connections). If the feedback voltage, Vf, is lower than the threshold voltage, Vt, then the dendritic connections will be strengthened. Because the feedback voltage is a function of both the axonal and dendritic connections, one scenario that cannot lower Vf below Vt is weak axonal connections and very strong dendritic connections. In other words, if the dendritic connections (to activated neurons) are very strong, then the axonal connections (to neurons needing activation) must be correspondingly stronger. This relationship is not linear. Thus, based on the foregoing, nanoconnections in layers preceding the output layer can modify themselves.

Referring again to FIG. 13 as an example, if the voltage at H1 decreases to a point below $V_t$ when S1 is closed, then either neuron C or D (or both) will require the activation of neuron A to achieve the desired output. When S1 closes, neuron A receives the voltage at H1 as feedback, which is below the threshold of the neuron. This causes the neuron to output zero, which can again be transmitted by feedback to the neuron's input. Now the neuron is locked in a feedback loop constantly outputting zero. This causes an electric field to be generated across the connections of C1, from positive activations of I1 and/or I2 (i.e., inputs 1304 and/or 1306) to neuron A. Now the nanoconnections causing the activation of neuron A are even stronger.

Note that connections could also form between activated pre-synaptic neurons and the neuron in question even if no initial connection is present, or if the post-synaptic neuron is inactivated. This last form of connection formation is important because it allows for a form of connection exploration. In other words, connections can be formed, and if the feedback mechanism finds it useful to match a desired input-output relationship, it will be strengthen. If not, it will be weakened. This allows neuron A to keep outputting a high signal that in turn allows the output neurons to match the desired output. The same argument can apply for neuron B, or any neuron in any layer preceding the output layer.

Although a general description of the process has been provided above, it is helpful to view the process from a generalized perspective. Again, assuming that no connections are present in any of the connection networks, assume that a series of input vectors are presented to the inputs of the network, and a series of output vectors are presented to the desired output, while the training wave is present. The training wave should be at a frequency equal or greater than the frequency at which input patterns are presented or otherwise the first few layers will not be trained and the network will be unable to learn the associations. The first layer connection network, analogous to C1 in FIG. 13, will begin to form connections, and continue to build connections until the sum of the connection hovers around the activation threshold for the succeeding neurons (amplifiers). Once C1 connections have been created, C2 connections can be created in the same manner, this time with the input signals coming from the neuron activations of the preceding neurons.

The connections can, just like C1, build up and hover around the threshold voltage for the succeeding neurons. This pattern of forming connections can generally occur until a signal is achieved at the output. Once a signal has been outputted, the feedback process begins and the training wave guides the feedback so that connections are modified strategically, from the output connection network to the input connection network, to achieve the desired output. The training is continued until the user is satisfied with the networks ability to correctly generate the correct output for a given input.

In evaluating a standard feed-forward multi-layer neural network, connections generally form between every neuron in one layer and every neuron in the next layer. Thus, neurons in adjacent layers are generally completely interconnected. When implementing this in a physical structure where connection strengths are stored as a physical connection, the architecture must be configured that allows for both total connectedness between layers and which also provides for the efficient use of space. In a physical neural network device, connections form between two conducting electrodes. The space between the electrodes can be filled with a nano-conductor/dielectric solvent mixture, which has been described previously herein. As an electric field is applied across the electrode gap,

connections form between the electrodes. A basic method and structure for generating a large number of synapses on a small area substrate is illustrated in FIG. 14.

FIG. 14 illustrates a pictorial diagram of a perspective view of a system 1400 that includes a synapse array 1401, which can be implemented in accordance with one embodiment of the present invention. The synapse array 1401 illustrated in FIG. 14 can be implemented as a physical neural network chip. Additionally, the configuration depicted in FIG. 14 can be referred to simply as a "synapse" chip. The use of the term "synapse" as utilized herein is thus analogous to use of the term synapse in the biological arts. Although not biological in nature, the functions of a synapse or synapse chip as described herein do have similarities to biological systems. A synapse is simply the point at which a nerve impulse is transmitted from one neuron to another. Similarly, a synapse chip can be configured as the point at which electrical signals are transmitted from artificial neuron to another.

The basic structure of a physical neural network device, such as a physical neural network chip and/or synapse chip, is depicted in FIG. 14. Synapse array 1401 (i.e., a synapse chip) can formed from a substrate 1404. By forming a gap 1402 between two plates P1 and P2 covered with electrodes, filled with a solution of nano-conductors and a dielectric medium (e.g., a dielectric solvent), it can be appreciated that connections can easily form between every input and every output by aligning vertically from one input electrode to a perpendicular output electrode. It is thus apparent that the input and output electrodes would include some sort of conducting material.

The input electrodes are indicated in FIG. 14 by input electrodes I1, I2, I3, I4 and I5. The output electrodes are indicated in FIG. 14 by output electrodes O1, O2, O3, O4, and O5. For a Appellant's synapse chip, a perpendicular field can be applied across the connection gap to weaken the connections, so that the connection strengths are fully controllable. Various placements of auxiliary electrodes, either on P1, P2, or both can accomplish this feature. Alternatively, the temperature could be maintained at an elevated level so that thermal energy can

break down connections. This last form, (i.e., temperature degradation), could provide the most elegant solution. During the learning phase, an increased voltage drop across the connections can result in substantial heat generation within the chip. This heat, in turn, can be vital to the learning process by weakening connections that \are not used.

FIG. 15 illustrates a pictorial diagram 1600 of a perspective view of an alternative chip structure 1601 with parallel conductors on output, which can be implemented in accordance with an alternative embodiment of the present invention. As indicated in FIG. 15, the actual chip layout can be seen as two basic chip structures, an input layer 1606 and an output layer 1604, each sandwiched over a gap 1602 filled with a nanoconductor/dielectric medium (e.g., a solvent, a solution, a gel, a liquid, etc) mixture. The output layer 1604 can generally be formed from output electrodes O1, O2, O3, and O4, while the input layer can be formed from input electrodes I1, I2, I3, and I4.

Although only four input electrodes and four output electrodes are illustrated in FIG. 15, this particular number of input and output electrodes is depicted for illustrative purposes only. In a typical synapse chip implemented in accordance with the present invention, many more (i.e., thousands, millions, etc.) input and output electrodes can be utilized to form input and output electrode arrays thereof. Additionally, the nanoconductors form connections in the intersections between input and output electrodes due to the increased electric field strength. Chip structure 1601 thus represents one type of a synapse chip, which can be implemented in accordance with one possible embodiment of the present invention described herein.

FIG. 16 illustrates a perspective view of a system 1700 that includes a connection formation 1701, in accordance with a preferred or alternative embodiment of the present invention. As depicted in FIG. 16, nanoconnections 1702 can form at intersections between input and output electrodes due to an increase in electric field strength. Architectures of this type can offer substantial benefits for producing a synapse chip. These include ease of assembly and efficient

use of space. Regarding the ease of assembly, the total chip can comprise two electrode arrays aligned perpendicular to each other, with a layer of nano-conductor/dielectric solution between the two.

FIG. 17 illustrates a system 1750 illustrating the use of system 1700 of FIG. 16 in the context of a synapse chip and neural network configuration thereof. System 1750 indicates a chip 1758 along with a top chip layer 1752 and a both chip layer 1754, which are respectively indicated through the use of solid lines (representing layer 1752) and dashed lines (representing layer 1754). A diagram 1756 represents connection conduits, while a schematic diagram 1756 represents graphically the mathematical operations taking place via chip 1758. Note that in FIGS. 16 and 17, like or analogous parts or elements are indicated by identical reference numerals.

A larger view of an adaptive network system can thus be seen in FIG. 17. As previously mentioned, a network can be constructed by integrating many base neurons (i.e., see schematic diagram 1756). Each base neuron can contain both temporal and a spatial summation of signals generated by other base neurons. This summed signal can then be compared to a threshold voltage, and if the summed voltage exceeds the threshold voltage, a pulse may be emitted at the base neurons pre-synaptic electrodes. The inverse of the pre-synaptic pulse can also be emitted at the base neurons post-synaptic electrodes.

The base neurons can be in a perpendicular array structure (i.e., chip 1758) composed of two or more layers 1752, 1754 coupled with synapses (i.e., system 1700). Each synapse can be composed of connection conduits, separated by a characteristic distance "d", where each connection conduit is the result of nano-particles aligning in an electric field generated by the temporal and sequential firing of the coupled base neurons (i.e., see schematic diagram 1756). External inputs to the network can be coupled to any post-synaptic electrode of any base neuron in any layer. And any network output can be provided at any pre-synaptic electrode of any base neuron in any layer.

Other attempts at creating a neural-like processor require components to be placed precisely, with resolutions of a nanometer. The design of FIG. 16, for example, only requires two perpendicular electrode arrays. Prepared nanoconductors, such as, for example, nanotubes and/or nanowires can be simply mixed with a dielectric medium (e.g., a dielectric solvent or solution such as a liquid, gel, etc.). A micro-drop of the solution can thereafter be placed between the electrode arrays. Regarding the efficient use of space, even with electrode widths of 1 micron and spacing between electrodes of 2 microns, 11 million synapses or more could potentially fit on 1 square centimeter. If electrode widths of 100nm, with spacing of 200nm, are utilized, approximately 1 billion synapses could potentially fit on 1 $cm^2$.

Although the electrode dimensions cannot be lowered indefinitely without a considerable loss in connection resistance variation, it is conceivable that a 1$cm^2$ chip could hold over 4 billion synapses (e.g., 50nm electrodes and 100nm spacing = 4.4 billion synapes/$cm^2$). Because neuron circuitry could potentially be constructed on the other side of the synapse arrays, very compact neural processors with high neuron/synapse density could also be constructed.

Some considerations about the construction of a chip should be addressed. For example, the distance between the input electrodes should generally remain at a distance close, but not touching, the output electrodes. If carbon nanotubes are utilized for the nano-conductors within the gaps, one would need to prepare the nanotubes to lengths shorter than the gap distance. If the gap distance is, for example, approximately, 100nm, then the nanotubes should be sized less this dimension. Given a diameter of about 1.5nm, nanotubes can only go so far, perhaps 10's of nanometers. At 1.5 nm, one is now approaching atomic distances. The distance between the two electrodes may be maintained by resting the upper plate of electrodes on "pedestals", which can be formed by an interference photolithography technique

Based on the foregoing it can be appreciated that embodiments are generally directed toward a physical neural network synapse chip and also a method for

forming such a synapse chip. The synapse chip disclosed herein with respect to one or more embodiments can be configured to include an input layer comprising a plurality of input electrodes and an output layer comprising a plurality of output electrodes, such that the output electrodes are located above or below the input electrodes. A gap is generally formed between the input layer and the output layer. A solution can then be provided which is prepared from a plurality of nanoconductors and a dielectric medium (e.g., a dielectric solvent or solution).

The solution can be located within the gap, such that an electric field is applied across the gap from the input layer to the output layer to form nanoconnections of a physical neural network implemented by the synapse chip. Such a gap can thus be configured as an electrode gap. The input electrodes can be configured as an array of input electrodes, while the output electrodes can be configured as an array of output electrodes.

The nanoconductors can form nanoconnections at one or more intersections between the input electrodes and the output electrodes in accordance with an increase in strength of the electric field applied across the gap from the input layer to the output layer. Additionally, an insulating layer can be associated with the input layer, and another insulating layer associated with the output layer. The input layer can be formed from a plurality of parallel N-type semiconductors and the output layer formed from a plurality of parallel P-type semiconductors.

Similarly, the input layer can be formed from a plurality of parallel P-type semiconductors and the output layer formed from a plurality of parallel N-type semiconductors. Thus, the nanoconnections can be strengthened or weakened respectively according to an increase or a decrease in strength of the electric field. As an electric field is applied across the electrode gap, nanoconnections thus form between the electrodes.

The most important aspect of the electrode arrays is their geometry. Generally, any pattern of electrodes in which almost every input electrode is connected to every output electrode, separated by a small gap, is a valid base for a connection network. What makes this particular arrangement better than other

arrangements is that it is very space-efficient. By allowing the connection to form vertically, a third dimension can be utilized, consequently gaining enormous benefits in synapse density.

FIG. 18 illustrates a schematic diagram of a system 1800 of electrode widths encoding specific synapses resistances, in accordance with an alternative embodiment of the present invention. As indicated in FIG. 18, a plurality of bottom layer electrodes 1810, 1812, and 1814 having different cross sections are located below a plurality of top layer electrodes 1802, 1804, 1806 and 1808. After the physical neural network or synapse chip is assembled, the maximum number of connections can be formed at each synapse, which is equivalent to the desired resistance at each synapse. Of course, the function relating to the cross-section area of the electrodes and the corresponding resistance will differ from substance to substance and will most likely have to be determined experimentally.

A synapse or physical neural network chip could therefore be produced with certain ready-made abilities, such as voice or facial recognition. After installation, it is up to the designer to create a product that can then modify itself further and continue to adapt to the consumer. This could undoubtedly be an advantageous ability. Utilizing the example of the cellular telephone, the cellular telephone could in essence adapt its speech-recognition to the accent or manner of speech of the individual user. And all of this is possible because the synapses are so space-efficient. Networks with very powerful pattern recognition abilities could fit into a tiny fraction of a hand-held device, such as, for example, a wireless personal digital assistant and/or a cellular telephone.

The embodiments described in Appellant's specification are thus directed toward a physical neural network that can be configured from a connection or a plurality of connections of molecules or molecular conductors, such as nanoconductors, such as, for example, nanowires, nanotubes, and/or nanoparticles. Such physical neural network can be implemented in the form of one or more synapse chips that can be combined with a neuron system (e.g., a neuron chip) of independent summing circuits.

The fundamental concept of a network or system (e.g., a synapse chip) is remarkably simple. When particles in a dielectric solution are exposed to an electric field (i.e., AC or DC), the particles can align with the field. As the particles align, the resistance between the respective electrodes decreases. The connection becomes stable once the electric field is removed. As the strength or frequency of the applied electric field is increased, the connections become increasingly aligned and the resistance further decreases. By applying a perpendicular electric field, one can also decrease the strength of the connections. Such connections can be utilized as "synapses" in a physical neural network chip (also referred to as a synapse chip), and the result is a neural network chip - a fully adaptable, high-density neural network chip.

Appellant's synapse can be configured in a manner that is highly appropriate for an adaptive neural network, which can also be referred to as an *adaptive integration network* or simply, an *adaptive network*. As indicated earlier, adaptive neural networks to date have been limited to software designs and/or conventional hardware implementations. Adaptive neural networks have not been designed or implemented based on nanotechnology components, systems, and/or networks as discussed herein.

FIG. 19 illustrates a schematic diagram of one example of an adaptive integration network 1900, comprising six interconnected processing elements, neurons 1910, 1920, 1930, 1940, 1950, and 1960. Although the adaptive integration network 1900 is illustrated as containing six neurons on a two-dimensional plane, it is to be understood that the present invention is not limited to the particular number of the neurons or to any particular network topology. In fact, implementations of an adaptive integration network may comprise hundreds, thousands, even millions of interconnected neurons. Neurons may be arranged in various physical and logical configurations, including but not limited to hexagonal, circular, rectangular, toroidal structures in one, two, three, or higher dimensions.

Each neuron 1910, 1920, 1930, 1940, 1950, and 1960 can be individually formed from standard photolithography or alternate procedures by building circuits

capable of neuronal function, as will be later discussed. Alternatively, connections between neurons 1910, 1920, 1930, 1940, 1950, and 1960 may be formed as nanoconductor(s) suspended within a dielectric solvent or solution. An example of nanoconnections that may be implemented to neurons 1910, 1920, 1930, 1940, 1950, and 1960 is provided by nanoconnections 304 of FIG. 3.

A neuron combined with pre-synaptic electrodes can thus be the basic processing element of an adaptive integration network and can be (although not necessarily) configured to receive signals from its "pre-synaptic" neurons as input and, in response, transmit output signals to its "post-synaptic" neurons. A neuron has two output states, firing or non-firing. In one embodiment, binary output signal values of $x_i = 1$ and $x_i = 0$ are assigned for the firing and non-firing states, some embodiments may employ non-binary values for the output signal $x_i$, for example, within a range $0.0 \leq x_i \leq 1.0$.

As another example, the value of the output signal $x_i$ can be 0.0 if the neuron does not "fire", and greater than or equal to 1.0 if the neuron does fire. In the context of electronic circuitry, the output of the neuron can comprise a voltage. When a neuron fires, that neuron could potentially cause its post-synaptic neurons to fire, as more specifically explained herein after, which could cause their post-synaptic neurons to fire, and so on, setting up a chain reaction along an active pathway.

Any neuron in an adaptive integration network can be designated as a data input neuron or a data output neuron. A data input neuron is a neuron that receives a signal external to the adaptive integration network, and a data output neuron is a neuron whose output signal is transmitted to a destination external to the adaptive integration network. Accordingly, external signals input into data input neurons may initiate a chain reaction of neuron firings throughout the adaptive integration network. When the neuron firings eventually affect the state of the data output neurons, the output of the adaptive integration network will change in response.

In the example of FIG. 19, neurons 1910 and 1920 are data input neurons because neurons 1910 and 1920 receive external input signals 1902 and 1904,

respectively. Neuron 1950 is a data output neuron because neuron 1950, when firing, produces an output signal 106. In this configuration, an asserted input signal 1902 eventually causes neuron 1910 to fire, which may then cause neuron 1940 and then neuron 1950 to fire, thereby producing the output signal 1906. Thus, the adaptive integration network 100 produces an output signal 1906 in response to an input signal 1902. In many implementations, it is convenient for data input neurons to only receive a single external signal and no internal signals as input.

In an adaptive neural network, a connection is the conduit along which a neuron receives a signal from another neuron. Connections can be formed between neurons in any direction to transmit a signal from an output of a pre-synaptic neuron to an input of a post-synaptic neuron. Typically, a neuron plays both roles, first as a post-synaptic neuron for receiving input signals from its pre-synaptic neurons, and second as a pre-synaptic neuron for generating output signals to its post-synaptic neurons.

For example, with continued reference to FIG. 19, pre-synaptic neuron 1910 is coupled to post-synaptic neuron 1940 by connection 1914, thus neuron 1910 is configured to transmit information to neuron 1940. In FIG. 19, neuron 1910 is also coupled to neuron 1920 by connection 1912; neuron 1920 is coupled to neuron 1930 by connection 1923; neuron 1930 is coupled to neuron 1940 by connection 1934 and to neuron 1960 by connection 1936; neuron 1940 is coupled to neuron 1950 by connection 1945; neuron 1950 is coupled to neuron 1910 by connection 1951 and to neuron 1960 by connection 1956; and neuron 1960 is coupled to neuron 1910 by connection 1961 and to neuron 1920 by connection 162.

Connections (e.g., nanoconnections) may be excitatory or inhibitory, through which transmitted signals respectively promote or retard the firing of the post-synaptic neuron in response. With continued reference to FIG. 19, excitatory a fully connected arrow represents connections, and inhibitory connections are illustrated with an offset, blocked arrow. For example, connections 1914, 1923, 1936, 1945, 1951, and 1962 are excitatory, and connections 1912, 1934, 1956, and 1961 are inhibitory.

Excitatory connections are used to transmit signals from one neuron to another in a feedback loop or other active pathway. Inhibitory connections, on the other hand, prevent neurons from firing and are useful in providing internal regulation among feedback loops, but cannot actually form a connection in a feedback loop. In the context of a physical neural network, the inhibitory connections may cause a momentary increase in the threshold voltage of the post-synaptic neuron, thereby inhibiting the activations of the neuron.

An adaptive integration network may be configured to include feedback loops. A loop is a closed circuit of linked excitatory connections arranged in the same circular direction. For example, adaptive integration network 1900 comprises two loops, a first loop with neurons 1910, 1940, and 1950 indicated with black excitatory connections 1914, 1945, and 1951, and a second loop with neurons 1920, 1930, and 1960 denoted with gray excitatory connections 1923, 1936, and 1962.

Loops are highly interactive with other loops. In general, a loop can be mutually reinforcing or mutually competitive with one or more other loops. The adaptive integration network 1900 depicted in FIG. 1 illustrates an example with two mutually competitive loops. If an input signal 1910 is applied causing neuron 1910 to fire in the first (black) loop, then a chain reaction is set up wherein neuron 1940 fires, then neuron 1950 fires, then neuron 1910 fires again, and so forth.

In addition, neurons 1910 and 1950 have inhibitory connections 1912 and 1956, respectively for suppressing firings of neurons 1920 and 1960, respectively, in the second (gray) loop. Thus, activation of the first (black) loop can force the deactivation of the second (gray) loop. Similarly, activating the second (gray) loop builds a circular chain of firings through neurons 1920, 1930, and 1960, while suppressing activity in neurons 1910 and 1940, via inhibitory connections 1961 and 1934, respectively.

Mutually interacting loops may be aggregated to form metaloops at a higher level of integration. For example, two mutually interacting loops may share one or more connections in common such that activity in one loop will affect the activity in

the other loop. Referring to FIG. 20, a portion of an adaptive integration network 2000 is depicted with two mutually interacting loops 2002 and 2004.

Loop 2002 comprises six neurons 2010, 2020, 2030, 2040, 2050, and 2060 connected in sequence, and loop 2004 comprises five neurons 250, 2060, 2070, 2080, and 2090 connected in sequence. Both loop 2002 and 2004 share neurons 2050 and 2060, which are coupled by connection 2056. Activity on either loop influences activity on the other loop. For example, if neuron 2010 in loop 2002 fires, that firing eventually results in the firing of neuron 2060, which transmits a signal to neuron 2010 of loop 2002 and to neuron 2070 of loop 2004. Similarly, if neuron 2070 in loop 2004 fires, that firing eventually results in the firing of neuron 2060, which transmits a signal to neuron 2010 of loop 2002 and to neuron 2070 of loop 2004.

As another example, one loop could branch off an active pathway to another loop, thereby initiating activity in the other loop. FIG. 21 illustrates a portion of an adaptive integration network 2100 with two loops 2102 and 2104. Loop 2102 comprises three neurons 2110, 2120, and 2130 connected in sequence, and loop 2104 comprises three neurons 2140, 2150, and 2160 connected in sequence. Furthermore, loop 2102 is connected to loop 2104 by a connection 2134 from neuron 2130 of loop 2102 to neuron 2140 of loop 2104. Activity in loop 2102, eventually results in the firing of neuron 2130, which sustains the activity of loop 2102 by transmitting an output signal to neuron 2110 of loop 2102 and initiates activity in loop 304 by transmitting the output signal via connection 2134 to neuron 340 of loop 2104.

Since an adaptive integration network provides much flexibility in configuration, it is to be understood that the present invention is not limited to any particular configuration of neurons and connections. Preferably, it is desirable to choose the number, distribution, and types of connections to maximize the total number of feedback loops while minimizing the functional constraints and interdependence of the loops. In general, this goal can be met by employing as many connections per node as feasible for a given implementation. The distribution

of connections can vary from implementation to implementation of an adaptive integration network. For example, a maximum length can limit connections so that distant neurons are not directly connected, and the assignment of connections can be determined randomly or in accordance with an algorithm designed to give each neuron a similar physical or logical arrangement.

In an adaptive integration network, a neuron fires in response to firings of the neuron's pre-synaptic neurons under certain conditions. More specifically, each neuron has an associated excitation level $\epsilon$, which is responsive to the signals received from the neuron's pre-synaptic neurons. The neuron can fire when the neuron's excitation level $\epsilon$ is greater than or equal to the neuron's threshold value, $\theta$. In the context of a physical neural network, this is accomplished with an integrator circuit, as will be described.

Furthermore, each connection can be characterized by a corresponding synaptic efficiency in transferring its signal, represented by a connection weight $w_i$, where i indicates the $i_{th}$ connection for the neuron. In the context of a physical neural network, the synaptic efficiency is a direct result of the alignment of the nano-conductors between pre-synaptic and post-synaptic electrodes, and the alignment is in turn a result of heightened activation.

In a hardware implementation, when a pre-synaptic neuron fires a signal to its post-synaptic neurons, the firing neuron causes the excitation level $\epsilon$ of the post-synaptic neurons to change by a factor directly related to the properties of an integrator, as discussed previously. After firing, the neuron's excitation level $\epsilon$ is reset to a base level. In a hardware implementation, a refractory pulse generator, as discussed, can accomplish this previously. If the neuron does not fire, on the other hand, the integrator preserves the neuron's excitation level $\epsilon$, so that the excitation level $\epsilon$ may accumulate over time and the neuron may eventually fire. In one embodiment, however, the excitation level $\epsilon$ is subject to a decay process, for example, by multiplying the current excitation level by an attenuation parameter in the range $0.0 \leq \alpha \leq 1.0$. In a hardware implementation, this could be accomplished, for example, by storing charge from synaptic activations in a

capacitor and allowing for a small leakage current that serves the function of the attenuation parameter.

In one embodiment, neurons may be subject to a refractory period in which the neuron's excitation level $\epsilon$ is forced to remain at the base level for a given period of time. During the refractory period, the activity of its pre-synaptic neurons does not affect the neuron's excitation level $\epsilon$. Consequently, the refractory period can serve to impose a limit on the maximum firing rate of the neuron. As previously discussed, the refractory pulse generator triggers the grounding of all post-synaptic electrodes, thereby playing a crucial role in network learning.

In a hardware implementation, the following sub-circuits that compose an individual neuron accomplish the refractory period. The inputs from synaptic activations are summed via an integrator, which allows the accumulation of signals over time. The integrated signal is passed to a threshold circuit, such as a comparator or operational amplifier that outputs a high or low voltage in response to the integrator signal being above a set threshold. This signal is passed to a circuit that allows a pulse of period "T" to be generated. The output pulse is the output of the neuron. This output is feed into a refractory pulse generator, which serves the purpose of grounding the post-synaptic electrodes in a synapse while the neuron is actively generating a pulse.

If the output pulse of the neuron was high, then the refractory pulse generator could comprise a NOT gate, for example. The grounding of the postsynaptic electrodes serves two purposed. First, the neuron is re-set to a zero level activation, as described earlier. Second, the lowered potential causes an increase in the electric field across all connection in a connection network currently activating the neuron. In other words, during the time of the refractory pulse, all the connections that are coming from firing neurons become stronger.

*Training* is generally the process of updating the nano-connections in an adaptive integration network so that the adaptive integration network produces desired outputs in response to inputs. In contrast with prior techniques involving artificial neural networks that employ distinct training and implementation phases,

training the adaptive integration network is constantly occurring during the normal operation of the adaptive integration network and is a direct result of feedback within the network.

Prior to operation of the adaptive integration network, the connection weights within the adaptive integration network are initialized, for example, either randomly or to a preset value. During the operation of the adaptive integration network, the connection weights are constantly strengthened or weakened, provided that the connection weight strengthening or weakening conditions are met. *Connection weight strengthening* refers to the process of decreasing the resistance of the nano-connection. Connection weight strengthening occurs whenever any two connected neurons fire in close temporal proximity, with the post-synaptic neuron firing after the pre-synaptic neuron, during the post-synaptic neurons refractory pulse period.

Optionally in some adaptive network implementations, connection weight strengthening occurs every time a neuron fires, but the magnitude of the connection weight strengthening is a function of the amount of time since the pre-synaptic neuron of the connection has fired. This is a natural result of frequency dependence on connection formation in Appellant's synapse since connections contributing less to the over-all activation of a neuron will receive fewer "refractory" pulses and consequently see a decreased frequency of electric field across the pre and post-synaptic electrode terminals.

Connection weight strengthening allows for frequently used neuronal pathways to be reinforced. As one neuron fires, the neuron produces an output signal that may induce one or more of the neuron's post-synaptic neurons to fire in close temporal proximity, thereby strengthening the connection between the neurons. Similarly, the firing of the post-synaptic neuron may cause that neuron's post-synaptic neuron to fire, creating a chain reaction of firing neurons along an active pathway. Since a connection weight increases when both the pre-synaptic and the post-synaptic neurons fire in close temporal proximity, each time the active neural pathway is used, the connection weights along the active pathway are increased.

A loop is a special case of a frequently used active pathway, because, once initiated, the neurons in the loop successively fire in cycles around the loop. Each time the neurons fire, their connections are strengthened, yielding a stable loop circuit. Consequently, the connection weight strengthening rules foster stable circuits of self-reinforcing loops, which can constitute stored memory of patterns and other information

*Connection weight weakening* generally refers to the process of decreasing the strength of the connection. In an adaptive network, connection weight weakening occurs after a specified period of passivity for the connection. A connection is considered "passive" for particular point in time if the post-synaptic neuron and the pre-synaptic neuron of the connection have not fired in close temporal proximity in that period of time. Thus, the connection weights for passive connections progressively weaken, reducing the influence of those passive connections in the adaptive integration network. In a physical neural network implementation, a decrease in synapse activations results in a lower frequency of applied electric field and thus a decrease in connection formation. As discuss previously, The connection formation could be constantly degraded by a perpendicular electric field or even from a dissolution process within the solution.

Larger connection weights are slowly decreased, thereby allowing for strong connections to remain more or less fixed, slow to decay even after prolonged passivity. This effect is naturally achieved in a network by a decrease in the local electric filed around a strong nano-connection, thereby weakening effects from perpendicular electric fields. Alternatively, a strong nano-connection results in higher van-der-wall attractions and a corresponding heightened resistance to dissolution within the dielectric medium. In an adaptive integration network, connection weights are constantly being adjusted during normal operation, for example, strengthened when two connected neurons fire in close temporal proximity or weakened after a period of passivity. Therefore, even mere use of the adaptive integration network causes the adaptive integration network to be fine-tuned.

In certain cases, however, it is desirable to cause the adaptive integration network to learn and adapt to new patterns and information. FIG. 23 illustrates a flowchart 2300 illustrating the operation of adaptive learning in accordance with one embodiment of the present invention. As illustrated in FIG. 23, adaptive learning can be fostered by presenting input data to the adaptive integration network, as indicated at block 2301. The input data causes neuron firings, leading to output data from output data neurons as the result.

As indicated at decision block 2302, a loop can be controlled long as the output data does not match the desired output. The network activity of the adaptive integration network can be increased, as depicted at block 2304, which causes the output data to change. When the desired data is produced, the network activity is restored to a normal level, as described at block 2306. Various techniques may be employed to increase network activity, i. e. the rate of neural firings, including threshold lowering and neural output signal magnification.

Network activity can be increased by lowering the thresholds of the neurons in the adaptive integration network. For example, the thresholds could be reduced by a fixed amount or proportion, such as to one half. Threshold lowering causes neurons to fire sooner, because the excitation level $\epsilon$ only needs to reach a lower threshold level. Consequently, firing rate of neurons in the adaptive integration network is increased and, hence, the network activities of the adaptive integration network.

Yet another technique for increasing network activity is to increase the magnitude of the neural signals. Each time a neuron fires, the excitation level $\epsilon$ of the post-synaptic neurons are increased by a much larger amount because the neural output signal $x_i$ is larger. Consequently, the threshold level of the neuron is reached much more rapidly, increasing the firing rate of neurons in the adaptive integration network and, hence, the network activity. This can be accomplished by increasing the supply voltage of the neuron circuitry while keeping the threshold voltage constant.

Increasing network activity enables for new active pathways to be explored. For example, a neuron that is adjacent to an active pathway, but not part of the active pathway, might not ordinarily fire because it has low connection strength for a connection to a neuron on the active pathway. In this case, the excitation level $\epsilon$ of the neuron does not sufficiently accumulate to the ordinary threshold level to fire, for example, due to a more rapid attenuation of the excitation level $\epsilon$ or to competing inhibitory inputs. A lowered threshold, however, may be low enough or the excitation level $\epsilon$ may accumulate rapidly enough to induce that neuron to fire, enabling a new active pathway to be branched off the main active pathway.

Increasing network activity can also cause an active pathway for one stable circuit to transform into an active pathway for another stable circuit. A stable circuit, which constitutes stored memory, information, or patterns within the adaptive integration network, represents a locally optimal position in the solution space (all possible outputs for all possible input). As a result, increasing network activity permits adaptive exploration through the solution space in search of other locally optimal positions for the new input/output data sets. Another result of increasing network activity is that the response time of the adaptive integration network is reduced, making the adaptive integration network faster.

FIGS. 24 and 25 illustrate how increasing network activity can dismantle an active pathway. Note that in FIGS. 24 and 25, like or analogous parts are indicated by identical reference numerals. Thus, In FIG. 24, a system 2400 includes an active pathway comprising neurons 2410, 2420, and 2430 with high connection weights of 0.7. The pathway that includes neurons 2440, 2450, and 2460 with low connection weights of 0.3, on the other hand, is inactive. Furthermore, the low connection weight of 0.3 for the connection between neuron 2410 of the active pathway and neuron 2440 means that neuron 2440 rarely fires, because the connection weight is too low to cause the excitation level $\epsilon_{2440}$ of neuron 2440 to sufficiently increase to reach the ordinary threshold level.

When network activity is increased, for example by lowering the threshold, the accumulated excitation level $\epsilon_{2440}$ is now high enough with respect to the

lowered threshold to cause neuron 2440 to fire in response to a firing of neuron 2410. When neuron 2440 fires, an output signal is transmitted to the neuron 2450, which also fires with the increased network activity. The firing of neuron 2450 induces neuron 2460 to fire and therefore strengthen their connection.

Neuron 2450, moreover, is the source of an inhibitory connection to neuron 2420 of the active pathway, which prevents neuron 2420 from firing so often. As both neuron 2450 and neuron 2420 fire, the inhibitory connection between the two neurons is strengthened, further preventing neuron 2420 from firing so often. Eventually, the passivity of neuron 2420 causes the connection between neuron 2410 and 2420 to weaken, completing the dislodging of the active pathway.

FIG. 25 illustrates the result of dislodging the active pathway, in which the new active pathway comprises neurons 2410, 2440, 2450, and 2460. FIG. 25 thus illustrates a system 2500 in which neurons 2420 and 2430 formerly were part of an active pathway, but are no longer, because their connection weights have been weakened. Adaptive learning can be initiated in response to an external signal from a user when the output is wrong, which is analogous to a biological pain signal. This external signal causes the network activity to be increased, for example, by lowering the threshold levels of the neurons. The increased network activity causes the input signals to be deflected or rerouted onto new active pathways and loops, thereby exploring new stable circuits.

These new pathways and loops will eventually affect the data output neurons and alter the output values. If the output values are still undesired, then the increase in the network activity is maintained, causing the new pathways and loops to be ephemeral and generating even newer active pathways and loops. As soon as the desired output is attained, the user can discontinue the network activity increasing signal, causing the relevant network parameters (thresholds, etc.) to rebound to their ordinary levels and ceasing the adaptive training. This process can be automated if the desired output is presented before hand so that the output of the adaptive integration network can be compared by computer with the desired output to generate the external signal.

In contrast with retraining methods for conventional artificial neural networks, including both software and hardware implementations thereof, adaptive learning with adaptive integration networks is less disruptive, particularly when implemented via nanotechnology devices and techniques, such as discussed herein. For example, with conventional artificial neural networks every neuron is perturbed during training, but with adaptive integration networks only the neurons along active pathways and their neighbors are affected.

Thus, only relevant connections are adjusted, and previously established but unrelated loops and meta-loops are left intact, which hold previously learned classifications and information. Therefore, in further contrast with conventional artificial neural networks, a nanotechnology-based adaptive integration network can learn new information and patterns at any time without having to relearn previously learned material or going through a new training stage.

FIG. 26 illustrates a flow chart 2600 of operations depicting logical operational steps for modifying a synapse of a physical neural network, in accordance with an alternative embodiment of the present invention. According to the operations generally illustrated in flow chart 2600 of FIG. 26, Appellant's synapse can be modified based on a neuron refractory period. The process is generally initiated, as indicated at block 2602. As depicted at block 2604, one or more signals can be output from a connection network formed for example, from nanoconnections, such as nanoconnections 304 of FIG. 3.

Such signals may be generated in the form of a voltage or a current, depending upon a desired implementation. For illustrative purposes only, it can be assumed that such signals comprise voltage signals. As indicated next at block 2606, these signals provided by the connection network can be summed by at least one neuron within the physical neural network and then, as illustrated at block 2608, compared to a threshold value. The threshold voltage can be an externally applied and modifiable voltage.

If, as indicated at block 2610, the current state of activation does not exceed the threshold value or threshold voltage, the process simply terminates, as

indicated at block 2611. If, however, the current state of activation does exceed the threshold value or threshold voltage, then the process continues, as indicated at block 2612, and a pulse (e.g., a voltage pulse or current pulse) is emitted from a neuron within the physical neural network. During this pulse, a "refractory pulse generator" grounds the postsynaptic junction thereof.

This operation in turn can cause the synapses receiving pre-synaptic activation to experience an increase in the local electric field. The pre-synaptic electrodes of succeeding neurons and post-synaptic connections of the pulse emitting neuron thus receive a pulse, as indicated at block 2615. Thus, synapses that contribute to the activation of the neuron can receive an increase in the local electric field parallel to the connection direction and can also experience a higher frequency of activation, two parameters that increase the strength nanoconnections thereof, as indicated at block 2618, and thus the strength of the synapse.

FIG. 27 illustrates a flow chart 2700 of operations illustrating logical operational steps for strengthening one or more nanoconnections of a connection network of a physical neural network by an increase in frequency, in accordance with an alternative embodiment of the present invention. Flow chart 2700 of FIG. 27 generally illustrates a process for strengthening nanoconnections (e.g., nanoconnections 304 of FIG. 3) of a physical neural network based on the close temporal proximity between two or more connected firing neurons. The process can be initiated, as indicated at block 2702, in which an initial (e.g., $i_{th}$) neuron is fired.

For illustrative purposes only, it can be assumed that the first neuron is fired. The firing of the first neuron causes an increase in the voltage of a pre-synaptic connection (e.g., a pre-synaptic electrode), as indicated at block 2708, and the an activation of a subsequent or second neuron, as illustrated at bock 2708, which in turn causes a refractory pulse to decrease the voltage of the post-synaptic connection (e.g., a post-synaptic electrode), as illustrated at block 2710. These operations in turn can generally result in an increased voltage between pre-synaptic electrodes and post-synaptic electrodes thereof, as depicted at block 2712. As

indicated at block 2712, the processes illustrated beginning at block 2704 can be repeated for subsequent electrodes.

The result of the operations described at blocks 2704 to 2712 occurring many times in succession can produce, as illustrated at block 2716, an increased frequency of the electric field between the pre-synaptic and post-synaptic electrodes, thereby causing, as depicted at block 2718, an increase in the alignment of nanoparticles (e.g., nanotubes, nanowires, etc.) and a decrease in the electrical resistance between electrodes thereof. The process can then terminate, as indicated at block 2720

One remarkably useful property of Appellant's synapse, which renders such a device very appropriate for an adaptive neural network, is that the frequency or magnitude of the electric field determines the connection strength. Thus, the connections that become frequently "activated" become stronger. The question of frequency dependence on synapse formation is actually a question of frequency dependence on alignment and connection formation, and can be viewed from at least two different perspectives.

Before further discussion, it will be helpful to make clear some terminology that will aid in the descriptions of the device. In the following descriptions, an adaptive network is built from one base neuron circuit. Each neuron circuit is fundamentally the same, and the network is build by connecting the base neuron circuits together to form certain topologies that result in desired properties, such as maximizing internal feed-back and memory retention. Thus, a complete description can almost be made by describing in detail the function and circuitry of an individual neuron circuit, and then studying how large numbers of the same base neuron will interact with each other. When the term "Neuron" is used, it refers to the electrical analog of a biological neuron, not a biological neuron. This includes summation properties, in time and space, and output properties (e.g., the ability to generate a relatively low-impedance output signal).

The connections between the pre-synaptic electrodes of one neuron and the post-synaptic electrodes of another neuron are formed via nano-connections, and

these connections can be seen as independent from either neuron. In other words, the connections do not belong to either neuron, but aid in the transfer of signals form one neuron to another. For example, when one says "positive activation of a pre-synaptic electrode", one is simply saying that the pre-synaptic electrode is raised to a positive voltage. With these clarifications, we can now proceed.

An adaptive network based on nanotechnology fabrication techniques can be based on, for example, the use of gold nanowires. Gold nanowires are not considered a limiting feature of the present invention, but are described herein for general illustrative and edification purposes only and also to indicate one possible embodiment of the present invention. Gold particles of gold ranging in a diameter of approximately 15nm to 30nm can be placed between electrodes deposited on a surface. When an alternating voltage is applied to the electrodes, thin metallic fibers begin to grow on the electrode edge facing the gap.

The fibers can grow in the direction of the other electrode until the gap is bridged, with the wires remaining in contact after the electric field is removed. Nanowire growth can be caused by particle aggregation at the tip of the fibers, thereby extending them toward the opposite electrode. The tip of the growing nanowire can create local electric fields of high intensity and gradient, giving rise to a dielectrophoretic force, which causes the aggregation.

Thus, a first perspective of synapse connection can be seen as a bridge-building process, occurring from one electrode to the other. This process can also be implemented utilizing carbon nanoparticles, such as carbon nanotubes and/or carbon nanowires. Because of their exceedingly small size, carbon nanotubes present a promising possibility because nanotubes have been found to form connections between electrodes. As the frequency increases from 0 Hz to 10's or even 100's of Megahertz, the standard deviation of angles of nanotubes from the electric field decreases. Thus, instead of a bridge-building process, universal alignment of all nanotubes can be implemented.

The nanotubes and/or nanowires and/or other molecular conductors (e.g., molecules), however, may join end to end to bridge a gap, because many carbon

nanotubes may overlap between two or more electrodes to form long ropes. With this in mind, the space between two electrodes can be viewed as a multiplicity of bridges between electrodes (conduits), each separated by a characteristic distance that is a result of the local disturbed electric field around each "bridge". Likewise, many conduits can bundle together to form a rope, bridging the electrodes.

By configuring nanotechnology-based neural circuitry, as described herein, which activates the connections required to be strengthened more frequently, while leaving the connections that need to be weakened inactivated, an adaptive network can be directly emulated utilizing artificial synapses that can both compute and store weight values. All that is required for such a network is a special type of neuron, modeled very much like that of a biological neuron. Each neuron can contain a number of separate functions. By connecting enough neurons into a topology that allows internal feedback, a modifiable network can be constructed which learns though an adaptive feedback process called adaptive integration learning.

As will be discussed later, these neurons can be constructed in conjunction with synapses to form highly interconnected networks, which use very little space on a VLSI chip. As one will see, such synapses lead themselves to a vertical stacking of planar chips, creating very high-density neural networks. The primary feature of an adaptive network is that of Hebbian learning. If the pre-synaptic neuron fires in close temporal proximity to the post-synaptic neuron, then the connections between the two (i.e., the synapse) can be strengthened. Similarly, if a synapse remains inactive for a long duration, then that connection can be gradually weakened.

Although this mechanism is by no means proven biologically, it provides a possible mechanism of how a cell can strengthen connections in a Hebbian manner, and can be considered the basis for an artificial neuron, which in turn can be used to build an adaptive network. In any case, some mechanism must be in place within a neuron so that its post-synaptic junctions know when they have contributed to neural activation. In an adaptive network utilizing Appellant's

synapses, for example, neurons that achieve a higher rate of activation can produce a higher-frequency (and magnitude) electrical field across their synaptic connections, thereby strengthening such connections. As one can see, the property of Appellant's synapse strengthening in proportion to an increase in the frequency of an electric field is seminal to the incorporation of Appellant's device or component into an adaptive network.

Although the connection modification process is the result of an overall applied frequency, it can also be seen as a very small incremental change for every activation of the synapse. An *activation* of a synapse can be seen as an activation of a pre-synaptic neuron at the same time as the activation of the post-synaptic neuron. This results in an increase in the electric field, and although the connection strengthening process works with applied *frequencies*, it can be regarded as an incremental change for every activation to aid in understanding the behavior of the circuit since it is very difficult to picture anything more than small time intervals when dealing with large networks operating at high frequencies and summing signals in a temporal manner over thousands of synaptic inputs.

Signals comprising a voltage from a connection network can be summed by a neuron, in a spatial *and* temporal manner, and compared to the threshold voltage. One should note that although the voltage from the connection network is shown forming a voltage divider with $R_b$, which then in turn is summed by the neurons summing circuits, any circuit that accomplishes the same take may be used. For example, an amplifying stage may be added, or the integrating function may become part of the temporal summing circuit. The components described herein are meant to outline basic parts for circuit operation, but are not intended to limit the scope and type of circuit embodiments and implementations thereof.

Evaluating an individual adaptive neuron, if the current state of activation exceeds the threshold voltage, then a pulse may be emitted. During this pulse, the RPG, "refractory pulse generator" grounds the post-synaptic electrodes. This causes the synapses receiving pre-synaptic activation to experience an increase in the local electric field. For example, suppose a pre-synaptic neuron just fired, and caused

the firing of the neuron. This means that the pre-synaptic electrode, which itself is connected to the pre-synaptic neuron which just fired, is now on the positive swing of the output pulse.

The neuron, once fired, can output the same pulse, but the RPG will turn it into a negative-going pulse at its post-synaptic electrode. Because the firing of the pre-synaptic neuron precedes that of the post-synaptic neuron, the respective synapse can see (i.e., experience) an alternating electric field. Thus, synapses that contribute to the activation of the neuron can receive both an increase in the local electric field parallel to the connection direction and, when applied many times over, can also experience a higher frequency of activation, two parameters that increase the strength of Appellant's synapse. For reasons that will become clear later, the neuron is allowed to source current only on the positive portion of the pulse and sink current on the negative portion of the pulse, where as the neuron cannot source or sink current if it is not activated (i.e., producing a pulse).

One important point to understand before we continue is that each neuron operates in a completely asynchronous mode. This results in every neuron being completely independent from the rest of the network, and consequently massively parallel networks can be built that rely on the emergent behavior of all the interconnected, independent neurons. General properties of the neurons in the network, such as threshold, refractory period and habituation, may be controlled externally via an external CPU. Such external inputs may affect how the network computes, but are not a source of computation in and of themselves.

Before a neuron can act on information coming from its post-synaptic activations, the signals must all be summed. This summation can be performed with, for example, a resistor, $R_b$, acting as a voltage divider. Summation can alternatively be accomplished with an operational amplifier circuit, which has the added benefit that parameters can be manipulated remotely. A summation circuit can lead to the ability to easily form inhibitory connections and even control the activity of excitatory and inhibitory connections by adjusting the gain of the excitatory and/or inhibitory amplifiers. In a physical chip structure, the area taken

(on the chip) for the implementation of a summation circuit, or the use of a one or more large resistor such as $R_b$, can be a deciding factor in what type of circuit is utilized. Many summations circuits exist, and it is anticipated that a circuit that offers both external control and low component count will be most desirable.

One of the most important features of an adaptive neuron is an integrator. The integrator can sum the signals in time, so that a signal received from one synapse in one instant can be added to a signal from another synapse a short time later. The integrator one uses in an adaptive neuron has a large influence on the behavior of the network. A good analogy is to consider a barrel with a small hole in the bottom, and a trigger that opens a large valve at the bottom of the barrel when the level of incoming water reaches a certain point or threshold. Thus, we can picture pulses of water filling the barrel, from various sources, and a constant leakage of water out of the barrel due to the small hole. If the rate of water into the barrel is greater than the leakage due to the hole, the water level will rise until it hits a point where the valve is triggered and the water is rapidly flushed from the barrel.

In this analogy, the integrator can be seen as the barrel (which stores inputs from past time periods) and the leakage hole, which serves to keep the integrator from accumulating water and firing over long lengths of time when little activation is present. Both of these parameters can be adjusted. The integrator can be built in a number of different ways, and it is the intent of this patent to cover all possible cases, with no preference toward any particular circuit. It is anticipated, for example, that the capacitance of the post-synaptic electrodes could be used as a stage in the construction of an integrator.

Some integrating circuits have been found to be more stable than others. The exact details of the integration circuit are not important for the description of the device described herein, in accordance with one possible embodiment of the present invention, because it is the intent of such an embodiment to cover generally all possible integrator circuits. It is believed that the type of integrator utilized can have a large effect on the performance of a network. Bi-stable integrators, for

example, can result in much more robust integrators than previous models. Thus, a bi-stable property may be emulated in the electronic circuitry of an integrator and incorporated into an adaptive neuron.

The next important sub-system of an adaptive neuron is a threshold circuit. This can be accomplished via a number of ways, but a comparator (i.e. Op-amp) provides the simplest example. If the output from the integrator circuit reaches a voltage equal or greater than a threshold voltage, the threshold circuit outputs a signal, which we will assume to be high but could also be low. The threshold circuit, in combination with the integrator and summation circuit, performs the temporal and spatial summations necessary for an adaptive neuron.

The next sub circuit is the pulse-generator. Because Appellant's described networks respond to applied frequencies of electrical fields, it is necessary to encode outputs via pulses. This idea fits nicely with the biological analogy where signals are transmitted as a series of action potentials traveling through axons and dendrites. The input to the pulse generator is the output from the threshold circuit. The output from the pulse generator is, as can be expected, a pulse. The width of the pulse can be determined by the designer of the circuit, or controlled externally.

For reasons that will become clear in the context of an adaptive network, the output of the RPG can be a high (+Vcc) pulse followed immediately by a low (-Vcc or ground) pulse if the neuron output pulse is a low pulse (-Vcc or ground) followed by a high (+Vcc) pulse. Likewise, the output of the RPG can be a low pulse (-Vcc or ground) followed by a high (+Vcc) pulse if the neuron output pulse is a high (+Vcc) pulse followed immediately by a low (-Vcc or ground) pulse.

The output of the adaptive neuron, as far as any post-synaptic neurons are concerned, is generally (although not necessarily) that of the pulse generator, with one small caveat. To implement the form of Hebbian learning via a refractory pulse, as mentioned previously, the adaptive neuron should be allowed to strengthen those post-synaptic synapses that are activated while the neuron is also activated. In other words, pre-synaptic neuron firings that are highly correlated with post-synaptic neuron firings should be strengthened. To accomplish this, a

refractory pulse generator can be introduced. The refractory pulse generator takes a positive input (+Vcc from the pulse generator output) and produces a negative (-Vcc or ground) pulse at the post-synaptic electrodes. Following the negative pulse, the refractory pulse generator creates a positive (+Vcc) pulse, which can serve to positively activate the post-synaptic connections immediately after the negative activation.

Alternately, the refractory pulse generator can produce a positive pulse followed by a negative pulse. If the output of the pulse generator is a positive pulse followed by a negative pulse, then the output of the refractory pulse generator can be a negative pulse followed by a positive pulse. The width of this positive pulse can be adjusted, but it can be assumed to be the same as the negative pulse to aid in the description. One can also think of the refractory pulse generator as an inverter of the pulse generator, the output of which projects to the post-synaptic electrode.

Connected to the pulse generator and refractory pulse generator and neuron output are two important sub-circuits, a Selective Current Sink and a Selective Current Source, which serve an important, although not immediately obvious purpose. When the pulse generator outputs a positive pulse, the Selective Current Source allows the neuron to source current. When the refractory pulse is negative, the selective current sink allows the neuron to sink current. If no pulse is present, i.e., the pulse generator is outputting zero, then the current sink and current source does not sink or source current, but leaves the pre-synaptic electrodes floating.

The importance of the Selective Current Sink will become clear when one considers the group behavior of many neurons in a perpendicular array structure, all highly interconnected. Such restrictions on adaptive neurons can restrict current flow to predominantly the pre-to-post synaptic electrode direction, which can also keep unwanted current flows and voltage drops occurring from activated post-synaptic electrodes to inactivated post-synaptic electrodes and also from activated pre-synaptic electrodes to inactivated pre-synaptic electrodes.

In biological neural networks, habituation of the individual neurons plays a large role in global network function. As such, it can be appreciated that such an electrical analog could provide useful computational properties. Biologically, a neuron needs to consume chemical resources to provide the energy to fire. When the resources run low, and the by-products overwhelm the cell, the neurons firing rate begins to slow down. Likewise, when the neuron has not fired for awhile, the chemical resources needed for energy production begin to stockpile, which causes them to fire at heightened frequencies in comparison to neurons that have fired more frequently and not built up chemical reserves. The electrical analog could be provided in many ways, such as making the threshold of the neuron a function of the neurons past firing history. This can be accomplished with digital and/or analog circuitry, as long as the synaptic electrodes receive the proper pulse.

On a superficial level, it ca be appreciated how such a Hebbian learning circuit generally functions. When pre-synaptic neurons activate the adaptive neuron, the refractory pulse generator grounds (i.e., or lowers to -Vcc) all of the post-synaptic electrodes, which can cause an increased electrical field across all connections with high pre-synaptic electrodes. Immediately after the negative activation, the refractory pulse generator positively activates the post-synaptic electrodes. Those pre-synaptic neurons just activated can sink a current for a brief time, because of the selective current sink at their output. Thus, the connections participating in the activation of the neuron will see a full-wave alternating electrical field of increased magnitude. When this process is repeated, selective connections (i.e., those with a temporal correlation in firing) will generally experience an increase in the strength and frequency of the electric filed, and consequently become stronger.

Synaptic connections that activate just before a neuron's activation becomes stronger can experience an increased alternating electric field parallel to connection direction. Additionally, synapses that fire after the neuron activates become weaker (via columbic repulsion), and connections that could result in more efficient signal transduction synapses that fire and do not activate the neuron become slightly stronger (i.e., experience a half-magnitude alternating electrical field). This last

form of connection modification provides a form of connection exploration within the circuit. Without a form of non-Hebbian connection formation, potentially useful connections would never form. In other words, for Hebbian learning to take place, the connections should already exist. Hebbian learning only "picks out" those connections that turn out to be useful, and destroys those that cause undesired outputs.

The pulse emitted from the neuron can also take on a variety of other forms, such as, for example, a sinusoidal pulse, triangular pulse, etc. A general concept of how the electric fields at a synapse functions can be obtained if one assumes that the frequencies of pre- and post-synaptic activations are not the same, and considers the beat-frequencies of the input and output wave-forms present at the input and output electrodes. In this case, the gradient of the voltages at the pre- and post-synaptic electrodes can be approximately equivalent to the electric field. Although the connections themselves play an important role in the local electric field, it can be assumed that the cross-sectional area of the pre- and post-synaptic electrodes is large compared to the size of nano-connections, so that this problem is minimized.

As indicated in the background section of this disclosure, researchers, researchers in the neuro-biological fields have been challenged with a need to develop a computationally efficient algorithm that can emulate a biologically realistic neural network. Specifically, researchers have attempted to develop a method, which would allow the efficient calculation of Spike-Timing Dependent-Plasticity (STDP), while also permitting fully interconnected networks. In STDP, timing between pre- and post-synaptic events can cause a net potentiation (LTP) or a net depression (LTD) of synapses. FIGS. 28 and 29 illustrate respective graphs 2800 and 2900 of varying STDP models.

Many biological studies have found a relationship between "*T*", the inter-spike interval and $\Delta g/g$, the fractional change in conductance in the synapses, which would indicate LTP or LTD. FIG. 28 illustrates a graph 2800 indicative of this relationship. Graph 2800 indicates that if the pre-synaptic pulse arrives after the

post-synaptic pulse, the synapses can be depressed (weakened) in an exponential manner. If the post-synaptic pulse arrives after the pre-synaptic pulse, then the synapse will potentiate, again with an exponential dependence on "*T*". Other biologically realistic models have predicted a dependence such as that provided in graph 2900 of FIG. 29. Thus, graph 2900 is symmetrical and strikingly different from that of graph 2800 of FIG. 28.

To achieve a computationally efficient STDP algorithm, every neuron outputs a characteristic pulse via its axon, after attaining a threshold value. Simultaneously, the neuron can emit a characteristic pulse via its dendrites. FIG. 30 illustrates a schematic diagram of a neuron 3000, including a dendritic pulse and an axonal pulse thereof. Such pulses accomplish two goals. First, the axonal pulses can cause the excitation or inhibition of other neurons. Second, interactions between dendritic and axonal pulses can determine updates to synapses. Each neuron can be designated as either excitatory or inhibitory, and the pulses can be designed so that the interaction of a dendritic pulse and an axonal pulse results in either potentiation or depression on the synapse, depending on the timing between the pulses.

An update to the synapse can be a function of the pre- and post-synaptic pulses. In general, the following rule can be applied: $\omega_{t+1}=\omega_t-(pre)(post)$, where *(pre)(post)* represents the product of the pre- and post-synaptic activation, as provided by a pulse. Consider the pulses 3100 depicted in FIG. 31. Two types of pulses are illustrated in FIG. 31, including an excitatory axonal pulse and an excitatory dendritic pulse.

Also, consider the configuration of FIG. 32, which illustrates a schematic diagram of two neurons 3200, identified as neuron "A" and neuron "B". Neuron "A" can emit a pulse down its axon, and neuron "B", when activated, can emit a pulse up its dendrite. When neurons "A" and "B" initiate pulses after activation, such as, for example, pulses depicted in FIG. 31, a configuration of pulses, such as pulses 3300 depicted in FIG. 33, can be achieved. In FIG. 33, T is generally a measure between the post-synaptic pulse (dendritic pulse) initiation and the pre-synaptic

pulse (axonal pulse). Note that in FIG. 33, the dashed lines generally represent a post-synaptic pulse (dendritic pulse), while the solid lines generally represent the pre-synaptic pulse (axonal pulse).

A similar but varying format can be followed in FIG. 35. If an update is provided at every time-step, and there are at least four time steps available per pulse, such a measurement is generally illustrated in graph 3400 of FIG. 34, which is a good fit to realistic biological models incorporating bio-chemical processes. FIG. 35 represents an alternative set of pulses 3500. As indicated at block 3502, other learning rules can be obtained by modifying the dendritic or axonal pulses. When the pulses 3502 are plotted, a graph 3600 as indicated in FIG. 36 can be generated, which is an approximation of another learning rule.

Thus, by varying the pulse shapes, many different learning rules can be implemented. By changing the pulse patterns, post synaptic, pre-synaptic or both, different learning rules can be obtained. For example, by using skewed gaussian pulses in place of square pulses in the previous example, one can obtain an exponential dependence on "T", instead of a linear. The examples provided herein with respect to the use of pulse generation and pulse shapes are merely examples of embodiments in which the present invention can be implemented are not considered limiting features of the present invention.

FIG. 37 illustrates a high-level block diagram illustrating a system 3700 comprising a network of nanoconnections 3708 formed between one or more respective input and output electrodes 3702 and 3704, in accordance with an alternative embodiment of the present invention. Nanoconnections 3708 are located within a connection gap 3710, which is illustrated generally by a dashed line in FIG. 37. Nanoconnections 3708 generally are formed as a plurality of interconnected nanoconnections. As indicated earlier, connection gap 3710 can be filled with a solution (e.g., a liquid, gel, etc.).

An individual nanoconnection may constitute a nanoconductor such as, for example, a nanowire(s), a nanotube(s), nanoparticles(s), or any other molecular structures (e.g., molecules). Nanoconnections 3708 can also be constituted as a

plurality of interconnected nanotubes and/or a plurality of interconnected nanowires. Similarly, nanoconnections 3708 can be formed from a plurality of interconnected nanoparticles (i.e. molecules).

A major problem with emulating a biologically realistic neural network models, with pulse-coded outputs and modifiable synapses, concerns the extremely computationally expensive nature of the calculations. Whereas every synapse in a biological network can modify itself individually according to simple rules such as STDP, any calculation must take into account the state of the entire system, in essence storing the state in memory and constantly updating it. Because of the largely serial nature of both modern computers and memory, this task can be extremely inefficient, resulting in simulations that take many hours, days, or even weeks to achieve only a few seconds of simulated "real time". In addition to the difficulties involved in simulation activities, knowledge of the general structure of biologically realistic networks is also limited.

Although synaptic plasticity rules may create a network that can learn and adapt to its environment, a major step in creating a truly useful network is determining a general structure that allows plasticity to further "tune" the circuit. Such a general structure is, for example, coded in the genome of every living organism. The more simple the organism, the more "hard-wired" the network. It is anticipated that many useful networks will be developed for relatively simple tasks that are currently being accomplished with lower-level organisms such as insects, reptiles and birds.

Evolution has determined general connection patterns over hundreds of millions of years, and encoded this in DNA. Unfortunately, it is not a simple matter of analyzing DNA to determining a general connection pattern. Nor can a brain be efficiently dissected to determine the connection patterns, simply because the fundamental synaptic plasticity rules may differ slightly, and with a different learning rule comes different connection patterns. In designing a pulsed network with modifiable connections, it is very important to allow every possible connection, but it is not desirable that every connection be "on". For example, the human brain

possesses about 100 billion neurons, but each neuron is connected to only 10,000 others.

Knowing which connections *should not be connected* is a problem that only evolution can solve. This would require the initialization of certain synapses (i.e., turning some synapse on, while leaving the majority of the others off) and then testing the network by subjecting it to stimulus characteristic to the environment in which it will be used. If the network performs the job well, those particular connections can be recorded, and then production may begin only for those connections that are allowed to form. It is very likely, however, that the synapses that are initialized on the first trial will not be adequate. If not, some connections must be turned "on," "off," or some combination thereof, perhaps in a random manner that mimics evolution, or perhaps in a systematic manner.

The new pattern of connections must be subjected to its environment, and evaluated as to its ability to perform the desired task. It can be appreciated that a standard computer processor cannot achieve the speed necessary to simulate every generation, because many generations will most likely need to be evaluated, and every generation must have a chance to adapt to its environment via STDP rules. The time required to evaluate one generation via standard computation methods would most likely take many weeks.

In essence, it is necessary to recreate millions of years of evolution and many thousands of generations. To accomplish this, a faster version of the environment should be provided, and the network must adapt at an appropriately speed-up rate. One can accomplish this feat with an adaptive network, but synapses musts be turned "on" and "off" for initialization at the beginning of every generation.

As indicated earlier, computer simulations of neural networks are too complicated and slow for efficient and useful applications. Such serial based algorithms must initialize connections and then run learning routines and then re-initialize, run again, and so forth. Certain connections are desired for initialization, while others simply must be turned off. System 3700 therefore presents a solution to this problem. A gate 3706 can be located adjacent to the connection gap 3710,

electrically insulated, and thus provide an electric field for nanoconnections 3708, which can be, for example, semi-conducting nanotubes, nanowires, nanoparticle and/or other molecular semi-conducting structures.

Gate 3706 can be formed from materials, such as, for example, aluminum, gold, and the like. Note that the gate 3706 can be insulated from the nanoconnections and/or other molecular semi-conducting structures with the connection gap 3710 by a material, such as, for example, silicon dioxide or other types of oxide insulators. Although silicon dioxide is shown utilized in the configurations of systems 3700 and 3800, it can be appreciated that other types of insulating materials may also be utilized in place of silicon dioxide and that the use of silicon dioxide is not a limiting feature of the embodiments disclosed herein. Other types of insulating material that could be utilized in place of silicon dioxide or which could potentially complement the use of silicon dioxide as an insulator include materials such as, for example, aluminum oxide, hafnium oxide, zirconium oxide, yttrium oxide and/or silicon dioxide mixed with transition or rare-earth metals such as zirconium and/or lanthanum. The use of silicon dioxide as an insulating material in FIGS. 37 and 38 herein is therefore presented for illustrative and exemplary purposes only.

Thus, system 3700 is comprised of semi-conducting nanoconnections 3708, rather than simply conducting nanoconnections and/or other conducting molecular structures. The semi-conducting nanoconnections 3708 can be formed from material such as, for example, carbon, silicon, indium phosphide, and so forth. An AC field can be formed across the connection gap 3710, and made to vary, thereby strengthening or weakening nanoconnections and accomplishing STDP rules.

Such a structure can be viewed as analogous to a field-effect transistor, in which the source and drain electrodes correspond to the pre- and post-synaptic electrodes, and which the gate effectively controls if the connection is on or off. What is different about this structure when compared to prior literature is that the resistance between the source and drain can be modified by aligning the nanoparticles with an alternating electric field across the source and drain

electrodes, thereby implementing the functionality of a synapse with the added ability that the synapse can be turned "on" or "off" with the gate voltage.

FIG. 38 illustrates a high-level block diagram illustrating a system 3800 comprising a network of nanoconnections 3708 formed between one or more respective input and output electrodes 3702 and 3704, in accordance with an alternative embodiment of the present invention. Note that in FIGS. 37 and 38, identical features or elements are indicated by identical reference numerals. Thus, system 3800 of FIG. 38 additionally includes logic circuitry 3718, which can be connected to gate 3706. Such logic circuitry 3718 can include devices such as NAND, NOR, OR, AND logic circuitry and so forth.

Logic circuitry 3718 can thus include additionally circuitry such as transistors, resistors, capacitors, and the like. The use of gate 3706 in association with nanoconnections 3708 permits the connections 3708 and/or connection network thereof to function as a transistor or a group of transistors for determining which individual synapses or groups thereof are to be identified as activated or deactivated. System 3700 of FIG. 37 and by extension, system 3800 of FIG. 38, permit individual synapses within the physical neural network thereof to be turned "ON" or "OFF". Thus, systems 3700 and 3800 can be utilized in the context of a developers chip or a training chip for initialization and/or re-initialization and training of the physical neural network formed thereof.

FIG. 39 illustrates a system 3900 which can utilize general Hebbian and anti-Hebbian learning rules, and can be adapted for use in accordance with an alternative embodiment of the present invention. System 3900 generally describes a neural network mechanism that can be applied to a physical neural network formed utilizing nanotechnology, as described herein. In general, Hebbian learning is based on the concept that neurons that are activated simultaneously should have synapses therebetween strengthened. Neurons that are not activated simultaneously should have shared synapses thereof weakened. Hebbian learning can thus be implemented in neural networks as a technique for modifying connection based on correlations in pre- and post-synaptic activity. Anti-Hebbian

learning is essentially the opposite of Hebbian-based learning techniques. In anti-Hebbian learning, the connections are weakened when connections and/or neurons are correlated in activity, and strengthened when pre- and post-synaptic activity is anti-correlated.

System 3900 generally includes a physical neuron 3902 which may form part of a physical neural network as indicated herein. Neuron 3902 can be formed utilizing nanotechnology and/or integrated circuit fabrication techniques as indicated herein. A plurality of weighted factors 3906 (i.e., "w") can be input to neuron 3902. In general, an input 3908 (i.e., "x"), which is also equivalent to pre-synaptic activity (e.g., pre-synaptic electrode activity) can be multiplied and summed to produce a value, y, which represents neuron activity, as indicated at block 3910. A delta weight factor Δw can be calculated via a Hebbian learning rule, which is indicated at block 3912. An anti-Hebbian learning rule is indicated at block 3914.

Ultimately, an update function f(y), which is indicated at block 3916, can be multiplied by xy and a learning factor to produce a value Δw which is updated based on the function f(y). Based on system 3900, it can be appreciated that synaptic learning amounts to an unsupervised rule that changes synaptic weight as a function of pre- and post-synaptic activity. Function f(y), for example, can be viewed as a mechanism that implements either Hebbian or anti-Hebbian learning based on post-synaptic neural activity. In terms of a physical neural network as described herein, pre/post synaptic activity can be a voltage, frequency or a combination thereof. Thus, a voltage gradient dependency can be utilized to implement Hebbian/Anti-Hebbian learning in a physical neural network based on nanotechnology as indicated herein. Alternatively, varying of pre/post synaptic frequency can also provide for Hebbian/Anti-Hebbian learning.

FIG. 40 illustrates a high-level block diagram of a system 4000 which can be implemented in accordance with an alternative embodiment of the present invention. System 4000 generally includes a physical neural network 4004, which can be configured utilizing nanotechnology as described herein. Such a physical neural network 4004 can comprise a plurality of molecular conductors (e.g.,

nanoconductors) as indicated herein, which can form connections between pre-synaptic and post-synaptic components of the physical neural network 4004. Additionally, a learning mechanism 4002 can be applied for implementing Hebbian/Anti-Hebbian learning via the physical neural network 4004. Such a learning mechanism 4002 can utilize voltage gradient dependencies to implement Hebbian and/or anti-Hebbian connection modification within the physical neural network 4004. Learning mechanism 4002 can also utilize pre-synaptic and post-synaptic frequencies to provide Hebbian and/or anti-Hebbian learning within the physical neural network 4004. Examples of nanoconductors which can be utilized to implement nanoconnections of the physical neural network 4004 include nanoconductors such as nanotubes, nanowires, nanoparticles and the like.

Based on the foregoing, it can be appreciate that embodiments disclosed herein describe a physical neural network that can be configured utilizing nanotechnology. Such a physical neural network can comprise a plurality of molecular conductors (e.g., nanoconductors) which form neural connections between pre-synaptic and post-synaptic components of the physical neural network. Additionally, a learning mechanism can be applied for implementing Hebbian learning via the physical neural network. Such a learning mechanism can utilize a voltage gradient or voltage gradient dependencies to implement Hebbian and/or anti-Hebbian plasticity within the physical neural network. The learning mechanism can also utilize pre-synaptic and post-synaptic frequencies to provide Hebbian and/or anti-Hebbian learning within the physical neural network.

## VI. GROUNDS OF REJECTION TO BE REVIEWED ON APPEAL

**-- ISSUE #1: Whether claims 1-7, 9-11, and 13-20 are anticipated by Thakoor et al., (hereinafter referred to as "Thakoor") (US 6,522,352), "Solid-state thin-film memistor for electronic neural networks" under 35 U.S.C. 102(b).**

**-- ISSUE # 2: Whether claims 8 and 12 are unpatentable over 35 U.S.C 103(a) over Thakoor as applied to claims 1-7, 9-11 and 13-20 above, and further in view of "Computational Nanotechnology with Carbon Nanotubes and Fullerenes," by Deepak Srivastava et al, hereinafter referred to as "Srivastava".**

## VII. GROUPING OF CLAIMS

Two (II) groups of claims are being appealed as follows:

**GROUP I CLAIMS:**

Group I consists of claims 1-7, 9-11, and 13-20. Claim 1 is independent. Claims 2-10 stand or fall with independent claim 1. Claim 11 is independent. Claims 13-16 stand or fall with independent claim 11. Claim 17 is independent. Claims 18-20 stand or fall with independent claim 17.

Independent claims 1, 11, and 17 stand rejected under 35 U.S.C. § 102(b) as being anticipated by Thakoor.

**GROUP II CLAIMS:**

Group II consists of claims 8 and 12. Claim 8 is a dependent claim, which depends from claim 1. Claim 12 is a dependent claim, which depends from claim 11. Claim 37 stands or falls with independent claim 16.

Dependent claims 8 and 12 stands rejected under 35 U.S.C. § 103(a) as being unpatentable over 35 U.S.C 103(a) over Thakoor as applied to claims 1-7, 9-11 and 13-20 above, and further in view of Srivastava.

## VIII. ARGUMENT

### APPLICABLE LEGAL STANDARDS

### 35 U.S.C. §102(b)

The relevant statute cited in rejecting Appellants' claims is 35 U.S.C. §102(b), Conditions for patentability; novelty and loss of right to patent. Section (b) is the basis of the rejections rendered by the examiner. Under 35 U.S.C. §102, section (b), a person is be entitled to a patent unless:

> (b) - the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States
> ---

### Prima Facie Anticipation

The Commissioner of Patents and Trademarks, acting through examining officials, bears the initial duty of supplying the factual basis supporting a rejection of a patent application, including a rejection based on anticipation. *In re Warner*, 379 F.2d 1011, 154 USPQ 173, 178 (C.C.P.A. 1967), *cert. denied*, 389 U.S. 1057 (1968). The courts have interpreted this initial duty as placing on the Commissioner and the examiner the burden of presenting a *prima facie* case of anticipation. *See In re King*, 801 F.2d 1324, 1327, 231 USPQ 136, 138-39 (Fed. Cir. 1986); *In re Wilder*, 429 F.2d 447, 450, 166 USPQ 545, 548 (C.C.P.A. 1970). As stated by the Board in *In re Skinner*, 2 USPQ 2d 1788, 1788-9 (B.P.A.I. 1986), "[i]t is by now well settled that the burden of establishing a *prima facie* case of anticipation resides with the Patent and Trademark Office."

A general definition of *prima facie* unpatentability is provided at 37 C.F.R. §1.56(b)(2)(ii):

> A *prima facie* case of unpatentability is established when the information *compels a conclusion* that a claim is unpatentable under the preponderance of evidence, burden-of-proof standard, giving each term in the claim its broadest reasonable construction <u>consistent with the specification</u>, and before any consideration is given to evidence which may be submitted in an attempt to establish a contrary conclusion of patentability. (Emphasis added.)

"Anticipation requires the disclosure in a single prior art reference of each element of the claim under consideration." *W.L. Gore & Associates v. Garlock, Inc.*, 721 F.2d 1540, 220 USPQ 303, 313 (Fed. Cir. 1983) (citing *Soundscriber Corp. v. United States*, 360 F.2d 954, 960, 148 USPQ 298, 301 (Ct. Cl.), *adopted*, 149 USPQ 640 (Ct. Cl. 1966)), *cert. denied*, 469 U.S. 851 (1984). Thus, to anticipate the Appellants' claims, either *Strandwitz* or *Mann* must disclose each element of the respective claims that they are being recited for. "There must be no difference between the claimed invention and the reference disclosure, as viewed by a person of ordinary skill in the field of the invention." *Scripps Clinic & Research Foundation v. Genentech, Inc.*, 927 F.2d 1565, 18 USPQ 2d 1001, 1010 (Fed. Cir. 1991).

To overcome the anticipation rejection, the Appellants need only demonstrate that not all elements of a *prima facie* case of anticipation have been met, *i. e.*, show that *Strandwitz* or *Mann* fails disclose every element in each of the Appellants' claims associated with the relevant reference used for their rejection. "If the examination at the initial state does not produce a prima face case of unpatentability, then without more the applicant is entitled to grant of the patent." *In re Oetiker*, 977 F.2d 1443, 24 USPQ 2d 1443, 1444 (Fed. Cir. 1992).

***Inherency-Based Anticipation***

There are a number of factors that must be considered when attempting to establish inherency as a basis for anticipation. Inherency should only be applied under very limited circumstances. That is, inherency permits in very limited circumstances, an invention to be anticipated by prior art that is lacking minor, well-known features in the claimed invention. If the "missing subject matter" is "inherent" or necessarily disclosed in the prior art reference, then anticipation can exist. As stated by the Federal Circuit (see In re Sun USPQ2d 1451, 1453 (Fed. Cir. 1983)

> ...To serve as an anticipation when the reference is silent about the asserted inherent characteristic, such gap in the reference may be filled with recourse to intrinsic evidence. Such evidence must make clear that the missing descriptive matter is necessarily present in the thing described in the reference and that it would be so recognized by persons of ordinary skill.

In this regard, the CCPA has added that "'[i]nherency, however, may not be established by probabilities or possibilities. The mere fact that a certain thing may

result from a given set of circumstances is not sufficient". See In re Oelrich, 666 F.2d 578, 581, 212 USPQ 323, 326 (C.C.P.A. 1981) (quoting Hansgrig v. Kemmer, 102 F.2d 212, 214, 40 USPQ 665, 667 (C.C.P.A. 1930). That is, the missing element or function must necessarily result from the prior art reference.

Additionally, when an Examiner's rejection relies on inherency, it is incumbent upon the Examiner to point to the page and line of the prior art that justifies the rejection based on an inherency theory. The Examiner must not leave the Appellant to guess at the basis of the inherency rejection.

The fact that a certain result or characteristic may occur or be present in the prior art is not sufficient to establish the inherency of that result or characteristic. *In re Rijckaert*, 9 F.3d 1531, 1534, 28 USPQ2d 1955, 1957 (Fed. Cir. 1993) (reversed rejection because inherency was based on what would result due to optimization of conditions, not what was necessarily present in the prior art); *In re Oelrich*, 666 F.2d 578, 581-82, 212 USPQ 323, 326 (CCPA 1981). "To establish inherency, the extrinsic evidence 'must make clear that the missing descriptive matter is necessarily present in the thing described in the reference, and that it would be so recognized by persons of ordinary skill. Inherency, however, may not be established by probabilities or possibilities. The mere fact that a certain thing may result from a given set of circumstances is not sufficient.' " *In re Robertson*, 169 F.3d 743, 745, 49 USPQ2d 1949, 1950-51 (Fed. Cir. 1999) (citations omitted).

"In relying upon the theory of inherency, the examiner must provide a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic necessarily flows from the teachings of the applied prior art." *Ex parte Levy,* 17 USPQ2d 1461, 1464 (Bd. Pat. App. & Inter. 1990) (emphasis in original).

**35 U.S.C. §103(a)**

The relevant statute cited in rejecting Appellants' claims is 35 U.S.C. §103(a),

(a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having

ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

**Prima Facie Obviousness**

The obligation of the examiner to go forward and produce reasoning and evidence in support of obviousness is clearly defined at M.P.E.P. §2142:

> The examiner bears the initial burden of factually supporting any *prima facie* conclusion of obviousness. If the examiner does not produce a *prima facie* case, the applicant is under no obligation to submit evidence of nonobviousness.

M.P.E.P. §2143 sets out the three basic criteria that a patent examiner must satisfy to establish a *prima facie* case of obviousness:

1. some suggestion or motivation, either in the references themselves or in the knowledge generally available to one of ordinary skill in the art, to modify the reference or to combine reference teachings;

2. a reasonable expectation of success; and

3. the teaching or suggestion of all the claim limitations by the prior art reference (or references when combined).

It follows that in the absence of such a *prima facie* showing of obviousness by the Examiner (assuming there are no objections or other grounds for rejection), an applicant is entitled to grant of a patent. *In re Oetiker*, 977 F.2d 1443, 1445, 24 USPQ2d 1443 (Fed. Cir. 1992). Thus, in order to support an obviousness rejection, the Examiner is obliged to produce evidence compelling a conclusion that each of the three aforementioned basic criteria has been met.

## APPELLANT'S ARGUMENTS REGARDING ISSUE #1 - ARGUMENTS IN SUPPORT OF PATENTABILITY OF GROUP I CLAIMS:

### Claims 1-7, 9-11, and 13-20 (Group I) are patentable over Thakoor.

Claims 1-7, 9-11 and 13-20 as amended on August 14, 2006, and entered by the USPTO, read as follows:

1. A system, comprising:

a physical neural network configured utilizing nanotechnology, wherein said physical neural network comprises a plurality of nanoconductors suspended and free to move about in a dielectric medium and which form neural connections between pre-synaptic and post-synaptic components of said physical neural network; and

a learning mechanism for applying Hebbian learning to said physical neural network.

2. The system of claim 1 wherein said learning mechanism utilizes a voltage gradient to implement Hebbian plasticity within said physical neural network.

3. The system of claim 1 wherein said learning mechanism utilizes voltage gradient dependencies associated with physical neural network to implement Hebbian learning within said physical neural network.

4. The system of claim 1 wherein said learning mechanism utilizes pre-synaptic and post-synaptic frequencies to provide Hebbian learning within said physical neural network.

5. The system of claim 1 wherein said learning mechanism utilizes a voltage gradient to implement anti-Hebbian plasticity within said physical neural network.

6. The system of claim 1 wherein said learning mechanism utilizes voltage gradient dependencies associated with physical neural network to implement anti-Hebbian learning within said physical neural network.

7. The system of claim 1 wherein said learning mechanism utilizes pre-synaptic and post-synaptic frequencies to provide anti-Hebbian learning within said physical neural network.

9. The system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanowires.

10. The system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanoparticles.

11. A system, comprising:

a physical neural network configured utilizing nanotechnology, wherein said physical neural network comprises a plurality of nanoconductors suspended and free to move about in a dielectric medium and which form neural connections between pre-synaptic and post-synaptic components of said physical neural network; and

a learning mechanism for applying Hebbian learning to said physical neural network wherein said learning mechanism utilizes a voltage gradient or pre-synaptic and post-

synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within said physical neural network.

13. The system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanowires.

14. The system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanoparticles.

15. The system of claim 11 wherein said dielectric medium comprises a dielectric liquid.

16. The system of claim 15 wherein said plurality of nanoconductors form physical neural connections when said dielectric medium is exposed to an electric field, such that said physical neural connections can be strengthened or weakened depending upon a strengthening or weakening of said electric field or an alteration of a frequency thereof.

17. A system, comprising:

a plurality of molecular conductors disposed in and free to move about within a dielectric medium comprising a dielectric solvent or a dielectric solution;

at least one input electrode in contact with said dielectric medium; and

at least one output electrode in contact with said dielectric medium, wherein said plurality of molecular conductors form physical neural connections when said dielectric medium is exposed an electric field across said at least one input electrode and said at least one output electrode, such that said physical neural connections can be strengthened or weakened depending upon a strengthening or weakening of said electric field or an alteration of a frequency thereof.

18. The system of claim 17 further comprising a physical neural network comprising said plurality of molecular conductors disposed within a dielectric medium comprising a dielectric solvent or a dielectric solution, said at least one input electrode in contact with said dielectric medium, and said at least one output electrode in contact with said dielectric medium.

19. The system of claim 18 further comprising a learning mechanism for applying Hebbian learning to said physical neural network wherein said learning mechanism utilizes a voltage gradient or pre-synaptic and post-synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within said physical neural network.

20. The system of claim 18 wherein said physical neural network is configured as an integrated circuit chip utilizing nanotechnology.

Regarding claim 1, the Examiner argued that Thakoor teaches a system, comprising:

a physical neural network configured utilizing nanotechnology (the Examiner cited "title" in support of this argument), wherein said physical neural network comprises a plurality of nanoconductors suspended and free to move about in a dielectric medium (citing page 3132, right column, lines 10-12; and page 3133,

right column, lines 3-5 Thakoor) and which form neural connections between pre-synaptic and post-synaptic components of said physical neural network (citing page 3132, left column, lines 24-41 of Thakoor in support of this argument); and

a learning mechanism for applying Hebbian learning to said physical neural network (the Examiner cited page 3133, left column, lines 1-14 of Thakoor in support of this argument).

The Appellant respectfully disagrees with this assessment. Thakoor does not teach, disclose, suggest and/or anticipate all of the claim limitations of claim 1 including: a physical neural network, nanotechnology, nanoconductors, a dielectric medium in which nanoconductors are free to move about, and a learning mechanism for applying Hebbian learning. Additionally, it is significant to note that the memistor device of Thakoor is neither a synapse nor a neural network. The memistor of Thakoor is also not an adaptive learning device but rather a programmable analog memory element.

Regarding the issue of a physical neural network, Thakoor discusses and discloses neural networks and neural network components in general but does not show or illustrate an actual physical neural network. The memistor of Thakoor is not a physical neural network or a synapse, as will be explained in more detail shortly. The left column, paragraphs 1-3, page 3132 of Thakoor generally discusses neural networks and neurons, but does not provide for an actual illustration or discussion of a specific neural network and how such a neural network would be implemented.

The remaining portions of Thakoor deal with a discussion of Thakoor's memistor device and illustrates at FIG. 3 of Thakoor, a circuit diagram of a circuit that performs an autonulling function, including the memistor in association with the neuron to be autonulled. The illustration of FIG. 3 of Thakoor, however, is not that of a physical neural network, but simply a neuron in association with Thakoor's memistor. Thakoor only indicates that the electrochemical analog memory of Thakoor effects of the memistor device "...in solid state devices are potentially useful in electronic neural networks for adaptive learning and optimization applications". In other words, the memistor is useful for use in a physical neural network, but in and of itself is not a physical neural network. The memistor is

merely one of many devices/components that could be adapted for use with a neural network. For example, a resistor is a device that finds usefulness in a neural network. Similarly, a transistor is a device that is useful in electronic neural networks. Such devices are in and of themselves not neural networks. By attempting to equate the memistor with a physical neural network, the Examiner is making an incorrect comparison to a device that is fundamentally different from a physical neural network. A more appropriate comparison for a memistor would be devices such as transistors or resistors that complement the use of a neuron or other physical neural network components.

Regarding the issue of nanotechnology, it is clear from a review of Thakoor that nanotechnology is not taught by Thakoor. The Examiner has asserted that Thakoor teaches nanotechnology and refers to the use of ions by Thakoor as a basis for this argument, asserting that the ions are inherently the same as Appellant's nanoconductors. The H+ ions of Thakoor and "ions" in general do not constitute nanoconductors/nanoparticles as taught by Appellant's invention and as these terms are known and considered in the nanotechnology arts. In order to understand why such "ions" are not nanoconductors/nanoparticles, the Appellant believes that it would be helpful to the Examiner to understand what actually constitutes "nanotechnology" and what does not. A general discussion of "nanotechnology" is provided in Appellant's "background" section of Appellant's specification as follows:

"The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. However, it is becoming increasingly difficult to increase the number of elements on a chip using present technologies. At the present rate, in the next few years the theoretical limit of silicon based chips will be reached. Because the number of elements, which can be manufactured on a chip, determines the data storage and processing capabilities of microchips, new technologies are required which will allow for the development of higher performance chips.

Present chip technology is also limited in cases where wires must be crossed on a chip. For the most part, the design of a computer chip is limited to two dimensions. Each time a circuit is forced to cross another circuit, another layer must be added to the chip. This increases the cost and decreases the speed of the resulting chip. A number of alternatives to standard silicon based complementary metal oxide semiconductor ("CMOS") devices have been proposed. The common goal is to produce logic devices on a nanometer scale. Such dimensions are more commonly associated with molecules than integrated circuits.

Integrated circuits and electrical components thereof, which can be produced at a molecular and nanometer scale, include devices such as carbon nanotubes and nanowires, which essentially are nanoscale conductors ("nanoconductors"). Nanoconductors are tiny conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Their structure and fabrication have been widely reported and are well known in the art. Carbon nanotubes, for example, exhibit a unique atomic arrangement, and possess useful physical properties such as one-dimensional electrical behavior, quantum conductance, and ballistic electron transport.

Carbon nanotubes are among the smallest dimensioned nanotube materials with a generally high aspect ratio and small diameter. High-quality single-walled carbon nanotubes can be grown as randomly oriented, needle-like or spaghetti-like tangled tubules. They can be grown by a number of fabrication methods, including chemical vapor deposition (CVD), laser ablation or electric arc growth. Carbon nanotubes can be grown on a substrate by catalytic decomposition of hydrocarbon containing precursors such as ethylene, methane, or benzene. Nucleation layers, such as thin coatings of Ni, Co, or Fe are often intentionally added onto the substrate surface in order to nucleate a multiplicity of isolated nanotubes. Carbon nanotubes can also be nucleated and grown on a substrate without a metal nucleating layer by using a precursor including one or more of these metal atoms. Semiconductor nanowires can be grown on substrates by similar processes."

The aforementioned language generally describes what is meant by "nanotechnology". Appellant's specification provides a number of examples of what constitutes "nanoconductors". Notice that the description above describes examples of nanoconductors as constituting tiny conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Page 22, paragraph [0088] of Appellant's specification further indicates the following:

Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules. A nanoconductor can also be implemented as, for example, DNA.

Of course, it is understood by those in the nanotechnology arts that variations to the aforementioned description of nanotechnology are likely to arise. Appellant's specification, however, can be utilized as a general guideline for the context of "nanotechnology" in which Appellant's invention is provided. As a

general rule, Appellant's claims need to be interpreted in light of Appellant's specification.

With this in mind, Appellant has provided various examples of nanoconductors in Appellant's specification. For example, the Appellant has referred to nanotubes, nanowires, nanoparticle and even DNA. For example, Appellant's specification at paragraph [0087] indicates that "...Examples of nanoconductors include devices such as, for example, nanowires, nanotubes, and nanoparticles". Appellant's paragraph [0087] also indicates that "The network of nanoconnections depicted in FIG. 3 can be implemented as a network of molecules, including, for example, nanoconductors." Appellant's specification at paragraph [0088) also indicates the following:

> "Nanoconnections 304, which are analogous to biological synapses, can be composed of electrical conducting material (i.e., nanoconductors). Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules."

Paragraph [0089] of Appellant's specification also indicates that carbon particles (e.g., granules or bearings) can also be utilized for developing the Appellant's nanoconnections. Such carbon granules or bearings therefore represent a type of nanoconductor. The various types of "nanoconductors" described above and by Appellant have several key features in common. First, they are not ions and are all multi-atom structures. Thus, Appellant's use of nanotechnology-based devices and components relates to multi-atom structures that are built (man-made or natural) or synthesized. DNA, for example, is a naturally constructed multi-atom structure. Ions are not such structures. An ion is simply a single charged atom. Atoms and atomic ions do not represent nanoparticles/nanoconductors because "nanotechnology" seeks to use atoms as the building blocks of multi-atom structures. If the use of an ion constituted "nanotechnology" then one could argue that any device that makes use of an ion is "nanotechnology". Ions are present in the use of car batteries, for example, but such car batteries would not be considered "nanotechnology".

In this light, the H+ ion of Thakoor is not a nanoconductor, but rather simply just that -- an ion. Thus, it is not proper to identify the ions of Thakoor as anticipating the nanoconductors of Appellant's invention because one skilled in the art would not recognize an ion as constituting such a nanoconductor (i.e., built or synthesized multi-atom structures such as DNA, nanotubes, nanowires, etc). Simply because a reference teaches the use of ions would not lead one skilled in the art to conclude that such ions are the same as components such as nanotubes, nanowires, DNA etc. In order to inherently anticipate Appellant's invention, the use of multi-atom structures such as DNA, nanotubes, nanowires and such nanoconductors must necessarily flow from the teachings of the Thakoor and in particular from the H+ ions as argued by the Examiner. It is clear that from a strict prima facie anticipation standpoint, that Thakoor does not disclose, teach or suggest nanotechnology-based nanoconductors such as nanotubes, nanowires, DNA, etc. From an inherency-based anticipation standpoint, it also clear Thakoor does not inherently anticipate the nanoconductors taught by Appellant's invention. This is so because Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of nanoconductors (e.g., nanotubes, nanowires, DNA, etc., as taught by Appellant's invention) necessarily flows from the teachings of the applied prior art, i.e., Thakoor's H+ ions.

Regarding the dielectric medium of Appellant's invention in which the nanoconductors are free to move about, there is no teaching, suggestion or disclosure of the use of such a dielectric medium with nanoconductors disposed therein by Thakoor. The Examiner cited page 3132, right column, lines 10-12; and page 3133, right column, lines 3-5 in support of the assertion that Thakoor anticipates a dielectric medium in which nanoconductors are free to move about.

Page 3132, right column, lines 10-12 indicates that "a thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serving as a hydrogen ion source is deposited by reactive magnetron sputtering".

Page 3133, right column, lines 3-5 indicates that "...since the $Cr_2O_3$ film serves as a source of H+ ions, its ability to absorb and retain water is crucial to the device operation".

The Examiner is therefore asserting that Thakoor uses chromium trioxide ($Cr_2O_3$) as a dielectric medium in which nanoconductors (as taught by Appellant's specification) are disposed and free to move about. This is simply not the case. The $Cr_2O_3$ of Thakoor is used as a hydrogen ion source and not as a dielectric medium. One of the key features of Appellant's claims is that Appellants nanoconductors are disposed and free to move about with Appellant's dielectric medium. Chromium trioxide as used by Thakoor is a solid. How can nanoconductors (e.g., nanotubes, nanowires, DNA, etc.) move freely about in a solid? In order to appreciate why the chromium trioxide of Thakoor is not used as a dielectric medium, the Appellant believes it would be helpful to discuss what a dielectric is and is not and also analyze some of the properties inherent to chromium trioxide.

A dielectric is a material that tends to concentrate an applied electric field within itself. As the dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. Thus, in order for the chromium trioxide of Thakoor to be used for the purpose of providing a dielectric medium, the chromium trioxide must be used for the purpose of concentrating an applied electric field within itself and other dielectric properties as indicated above. Again, Thakoor is not using the chromium trioxide for this purpose. Thakoor is using the chromium trioxide as a hydrogen ion source as part of an electrolytic electrochemical process/system, as opposed to the dielectric electromechanical process/system of Appellant's invention.

Additionally, the chromium trioxide ($Cr_2O_3$) of Thakoor is described by Thakoor as being hygroscopic. A "hygroscopic" is something that attracts water. $Cr_2O_3$ is a solid. The hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor tends to attract water, which could actually damage Appellant's nanoconductors and/or chip surface because when chromium trioxide is mixed with water it forms a strong acid. Note also that by adding more water to chromium trioxide, more hydrogen ions will be produced, which makes a for a good hydrogen ion source, but will also make for a very strong acid.

Such an acid will corrode and damage Appellant's nanoconductors (e.g., DNA, carbon nanotubes, gold nanowires, etc). Thus, it would not make sense to incorporate chromium trioxide into a device such as Appellant's invention that utilizes such nanoconductors because the nanoconductors, when in contact with the acid will become damaged. The use of chromium trioxide clearly does not necessarily lead to the use of the dielectric medium of Appellant's invention.

Additionally, it is important to note that use of H+ ions and the thin film of hygroscopic chromium trioxide in order to achieve the memistor of Thakoor is <u>electrolytic</u> in nature. Thakoor clearly states that the thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serves as a hydrogen ion source (see Page 3132, paragraph under heading "Experimental Details" of Thakoor). The Thakoor device is thus based on an electrolytic configuration, that is, the use of an electrolyte and not a dielectric. Thakoor, for examples, at page 3133, second column, third paragraph, specifically refers to the use of an electrolyte. The memistor of Thakoor is based on the use of the electrochemical process of electrolysis, which is the production of chemical changes by the passage of current through an <u>electrolyte</u> (not a dielectric).

An example of such an electrochemical process is described in the "Introduction" section of Thakoor, Page 3132, Column 1, lines 34 to Column 2, line 2, where Thakoor states that "...in this paper, we report on the operational characteristics and application potential of a solid-state 'memistor," an analog memory device based on the electrochemical ion transport to/from tungsten oxide in a thin-films structure. The three-terminal devices utilizes a reversible transfer of metal (hydrogen) ions in tungsten oxide..." The use of <u>electrolytes</u> is taught, for example, on page 3133, column 1, lines 24-26 of Thakoor where Thakoor refers to "$WO_3$/<u>electrolyte</u> display". The memistor of Thakoor is based on the production of chemical changes by the passage of current through an <u>electrolyte</u>.

An electrolyte is a substance containing free <u>ions</u> which behaves as an electrically conductive medium unlike a dielectric, which is an electrical insulator, i.e., a substance that is highly resistant to electric current. Electrolytes are generally composed of ions in a solution of some sort. The use of free ions for a substance that behaves as electrically conductive medium, differs from that of a

dielectric, which tends to concentrate an applied electric field (e-field) within itself. This is a fundamental and key difference between Thakoor and Appellant's invention. Unlike an electrolyte, such as that employed by Thakoor, as a dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. This is not true of electrolytic materials such as that used to create the memistor of Thakoor. This also not true of the hygroscopic chromium trioxide ($Cr_2O_3$) material of Thakoor, which is not used by Thakoor as a dielectric but is used as a hydrogen ion source.

Thus, to summarize, Thakoor's device is based on the use of electrolytes and a material ($Cr_2O_3$) that is not used as a dielectric but is instead used as a hydrogen ion source. The hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor tends to attract water, which would actually damage the nanoconductors as indicated previously.

Based on the foregoing, it can be appreciated from a strict prima facie anticipation standpoint, Thakoor does not disclose the use of a dielectric medium taught by Appellant's invention. From an inherency-based anticipation standpoint, it is also clear that Thakoor does not inherently anticipate Appellant's use of the dielectric medium. That is, based on the requirements of establishing inherency as a basis for anticipation, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor does not inherently anticipate the use of the dielectric by of Appellant's invention, because in relying upon the theory of inherency, the Examiner has not provided a basis in fact and/or technical reasoning to reasonably supporting the determination that the allegedly inherent characteristic of the use of a dielectric medium in which nanoconductors are free to move about necessarily flows from the teachings of the Thakoor reference.

Regarding the issue of neural connections formed between pre-synaptic and post-synaptic components of the physical neural network, the Examiner cited page 3132, left column, lines 24-41 of Thakoor. The Examiner has cited page 3132, left column, lines 24-41 of Thakoor but has not identified, which specific components of Thakoor constitute pre-synaptic and post-synaptic components. Again, the Examiner has cited a general discussion of neural network components but has not actually cited where and how Thakoor specifically discloses a physical neural

network and also pre-synaptic and post-synaptic components of a physical neural network. FIG. 3 of Thakoor, for example, is not a physical neural network. There is not even a synapse shown in FIG. 3 of Thakoor. Rather, what is shown is an autonulling neural node void of synapses. There are thus not even pre-synaptic and post-synaptic terminals in FIG. 3 of Thakoor. The Appellant cannot find any where in Thakoor where pre-synaptic and post-synaptic terminals are present, particularly given the fact that the memistor of Thakoor is a three-terminal device and a device containing pre- and post-synaptic terminals necessarily requires only two electrodes (i.e., one input and one output).

Regarding the issue of a learning mechanism for Hebbian learning, the Examiner cited page 3133, left column, lines 1-14, which states the following:

> "...electrodes, the electric field drive H+ ions from the Cr2O3 toward the cathode WO3. The injection of H+ ions (protons) into the WO3 (insulating) layer results in the formation of conducting HxWO3 (tungstic acid). The rate of formation of HxWO3 depends primarily on the control voltage. The above process can be reversed by an application of a negative control voltage (with respect to the read electrodes). In the reverse process, anodic dissociation of HxWO3 proceeds with the liberation of hydrogen. The rate of dissociation can also e varied with the magnitude of the control voltage....the reistance of the devices was measured with the control electrode at ground potential and a small voltage (~ 100 milivolts) applied across the read electrodes".

How is this <u>learning</u>? How is this a <u>learning</u> mechanism? How does the foregoing description cited by the Examiner constitute <u>Hebbian</u> learning? To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of any <u>learning</u> mechanism. Learning does not constitute programming the device. Thakoor on page 3133, left column, lines 1-14 merely describes the electrochemical process involved for programming the memistor of Thakoor. This does not describe learning or adaptability because in order for the internal state of the Thakoor memistor to change, a voltage must be provided on the gate electrode. This voltage can only come from an external circuit. Therefore the description on page 3133, left column, lines 1-14 of Thakoor cited by the Examiner as a basis for "learning" could not possibly learn without the addition or help of an external circuit. Page 3133, left column, lines 1-14 merely describes the rate of disassociation of hydrogen ions in the context of a controlled voltage for programming the memistor. It should be

pointed out that the word "control" implies a controller, which is not detailed in the description and required for learning. The Appellant's invention on the other hand, can adapt in the absence of a control circuit. Thakoor thus provides no basis for learning, let alone Hebbian learning.

In order to understand what Hebbian learning is, the Appellant believes it would be helpful to provide a brief overview of Hebbian learning.

Hebbian learning is based on Hebbian theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Introduced by Donald Hebb in 1949, it is also called Hebb's rule and is referred to as Hebbian learning as well.

From the point of view of artificial neurons and artificial neural networks, Hebb's principle can be described as a method of determining how to alter the weights between model neurons as a function of their correlations of their activity in time. The weight between two neurons will increase if the two neurons activate simultaneously (they are correlated); it is reduced if they activate separately. Nodes which tend to be either both positive or both negative at the same time will have strong positive weights while those which tend to be opposite will have strong negative weights. It is sometimes stated more simply as "neurons that fire together, wire together."

This original principle is perhaps the simplest form of weight selection. While this means it can be relatively easily coded into a computer program and used to update the weights for a network, it also prohibits the number of applications of Hebbian learning, at least with respect to software simulations of neural networks. This is because large neural networks contain massive numbers of synapses and the modification of the synapse in the traditional computing paradigm requires accessing memory. This memory access requires extraordinarily more energy than a physical neural network where synaptic states do not have to be "accessed". Today, the term *Hebbian learning* generally refers to some form of mathematical abstraction of the original principle proposed by Hebb. In this sense, Hebbian learning involves weights between learning nodes being adjusted so that each

weight better represents the relationship between the nodes. As such, many learning methods can be considered to be somewhat Hebbian in nature.

The following is a formulaic description of Hebbian learning: (note that many other descriptions are possible)

$$w_{ij} = x_i x_j$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$ and $x_i$ the input for neuron $i$. Note that this is pattern learning (weights updated after every training example). In a Hopfield network, connections $w_{ij}$ are set to zero if $i = j$ (no reflexive connections allowed). With binary neurons (activations either 0 or 1), connections would be set to 1 if the connected neurons have the same activation for a pattern.

Another formulaic description is:

$$w_{ij} = \frac{1}{n} \sum_{k=1}^{p} x_i^k x_j^k ,$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$, $n$ is the dimension of the input vector, $p$ the number of training patterns, and $x_i^k$ the $k$th input for neuron $i$. The Appellant invites the Examiner to view the following web site, which contains a good general overview of Hebbian learning:

http://en.wikipedia.org/wiki/Hebbian_learning

Based on a review of Thakoor and a basic understanding of what constitutes "learning" and specifically, Hebbian learning, it is very clear that Thakoor does not provide for <u>any</u> teaching, suggestion or disclosure of Hebbian learning. Additionally, it is very clear that Thakoor does <u>not</u> inherently anticipate Hebbian learning, and thus the Hebbian learning mechanism taught by Appellant's specification. The Examiner has not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory". Hebbian learning does not necessarily flow from page 3133, left column, lines 1-14 of Thakoor as the Examiner argues.

Regarding claim 2, the Examiner argued that Thakoor teaches the system of claim 1 wherein said learning mechanism utilizes a voltage gradient to implement Hebbian plasticity within said physical neural network (the Examiner cited Thakoor, Figure 2 in support of this argument). The Appellant notes that the arguments presented above against the rejection to claim 1 also apply equally to the rejection to claim 2 because claim 2 depends from claim 1.

FIG. 2 of Thakoor does not teach, suggest or disclose a learning mechanism, and specifically provides no teaching, suggestion or disclosure of Hebbian plasticity. The Examiner has stated Thakoor utilizes a voltage gradient to implement Hebbian plasticity. However, there is no teaching in Thakoor of plasticity let alone a complicated neural process such as Hebbian plasticity. FIG. 2 of Thakoor cited by the Examiner is simply a plot of resistance versus time for several control voltages for a turning the memistor device of Thakoor "on" and "off". FIG. 2 does not suggest, disclose or teach any sort of "learning" or "unlearning". FIG. 2 merely describes "turn-on" and "turn-off" characteristics of the Thakoor device, and does not illustrate a device that has the ability to develop or adapt in response to its environment. FIG. 2 of Thakoor merely shows two plots, one describing the turn-on programming voltage and another plot that describes a turn off programming voltage. For example, page 3133, left column 3rd paragraph of Thakoor merely describes the turn-on and turn-off characteristics of memistor with respect to the FIG. 2 illustration.

The Examiner's arguments with respect to FIG. 2 of Thakoor do not adequately explain how one skilled in the art would identify FIG. 2 as illustrating plasticity and more importantly, Hebbian plasticity or anti-Hebbian plasticity and/or the performance of any sort of "learning" or "unlearning". The word "Hebbian" does not actually appear anywhere in the Thakoor reference. "Hebbian" plasticity is not even implied anywhere in Thakoor. In order to demonstrate Hebbian plasticity by Thakoor, it would be necessary to show how correlations or anti-correlations in voltage signals on the Ni electrodes in FIG. 1 of Thakoor result in a conductance increase or decrease. This is not demonstrated by FIG. 2 of Thakoor and in fact is not demonstrated at all anywhere in Thakoor. FIG. 2 of Thakoor provides disclosure, hint or teaching of Hebbian plasticity.

Based on the foregoing, the Appellant submits that there is simply not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian plasticity or anti-Hebbian plasticity flows from the teachings from the test device programming characteristics for variations in resistance of test device with time for several different control voltages of Thakoor's FIG. 2. Plasticity and Hebbian plasticity in particular are very specific types of neural network features, and there is clearly not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian plasticity <u>necessarily</u> flows from the teachings from Thakoor. Thus, FIG. 2 of Thakoor does not inherently anticipate Hebbian and/or anti-Hebbian plasticity, or learning/unlearning and not even plasticity.

Regarding claim 3, the Examiner argued that Thakoor teaches the system of claim 1 wherein said learning mechanism utilizes voltage gradient dependencies associated with physical neural network to implement Hebbian learning within said physical neural network (the Examiner cited Thakoor, Figure 2 in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 1 apply equally to the rejection to claim 3 because claim 3 depends from claim 1.

Again, as indicated earlier, Thakoor does not disclose, teach or suggest Hebbian learning and Hebbian learning does not necessarily flow from the teachings of Thakoor. Furthermore, Figure 2 of Thakoor does not describe a learning mechanism as taught by Appellant's invention, and also does not provide for any teaching whatsoever of "Hebbian learning" as taught by Appellant's invention. Instead, Figure 2 of Thakoor only illustrates a graph of resistance versus time (in minutes), and <u>programming</u> characteristics based on resistance versus time with respect to various voltages. The Examiner argued that FIG. 2 of Thakoor utilizes voltage gradient dependencies to somehow provide for a teaching of Hebbian leaning (by citing FIG. 2 of Thakoor). <u>It might be helpful to the Examiner to make the distinction between a voltage gradient and a voltage</u>. A gradient is a spatial derivative, which means that a voltage gradient is how much the voltage changes across a distance. <u>This is not equivalent to voltage</u>. By referencing FIG. 2 as an example of a voltage gradient dependence is like saying that the slope of a

mountain is equal to its height. FIG. 2 clearly states the resistance of the Thakoor memistor is dependent on voltage, not voltage gradient.

FIG. 2 is thus not a learning mechanism or Hebbian learning as taught by Appellant's claim 3. FIG. 2 merely demonstrates that the memistor can achieve device programmability over a wide range of resistances, but not actual learning. FIG. 2 relates to the ability of the memistor to exhibit electrochemical analog memory effects, but not actual learning and clearly not plasticity or Hebbian plasticity. In fact, Thakoor specifically states that the memistor is an analog memory device. The memistor is simply a reprogrammable RESISTOR with memory, but is not a learning device. The storage of data (i.e., a memory) is not "learning". The memistor is thus a device for storing data, and not a device that learns and also exhibits Hebbian ***plasticity***. The memistor has characteristics of resistor but again does not exhibit Hebbian plasticity. For example, page 3132, left column, lines 38-39 of Thakoor specifically notes that the memistor is a memory device.

Regarding claim 4, the Examiner argued that Thakoor teaches the system of claim 1 wherein said learning mechanism utilizes pre-synaptic and post-synaptic frequencies to provide Hebbian learning within said physical neural network (the Examiner cited page 3132, left column, lines 24-41; and page 3133, left column, lines 1-14 in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 4.

Page 3132, left column, lines 24-41 describes generally how in electronic implementations of neural networks, neurons can be modeled as thresholding nonlinear amplifiers and that synapses can function as resistive interconnects. Page 3132, left column, lines 24-41 also describes a memistor as being a reprogrammable resistor with memory, and hence an analog memory device. There is no teaching here, however, that the memistor of Thakoor possesses pre-synaptic and post-synaptic components or even functions as a neural network. There is also no mention here of pre-synaptic and post-synaptic frequencies. The word "frequency" does not even appear nor is implied at Page 3132, left column, lines 24-41 of Thakoor cited b the Examiner. It is not clear how and why Hebbian

learning is even implied by Page 3132, left column, lines 24-41 of Thakoor. It is not clear how one skilled in the art would interpret Page 3132, left column, lines 24-41 to imply Hebbian learning. The same arguments apply essentially against the citation of page 3133, left column, lines 1-14 of Thakoor by the Examiner.

Regarding claim 5, the Examiner argued that Thakoor teaches the system of claim 1 wherein said learning mechanism utilizes a voltage gradient to implement anti-Hebbian plasticity within said physical neural network (the Examiner cited Figure 2 of Thakoor in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 5. <u>How</u> is the voltage gradient of Thakoor used to implement <u>anti-Hebbian</u> plasticity? How does <u>anti-Hebbian</u> plasticity necessarily flow from FIG. 2 of Thakoor?

It is not clear how the features of Thakoor the Examiner cited with respect to page 3133, left column, lines 1-14 constitute a "learning mechanism" and specifically <u>anti-Hebbian</u> learning. The Appellant does not understand how and why anti-Hebbian learning is accomplished by "the growing or lessening the conductivity of the resistance put a field to adjust the memory" of Thakoor as argued by the Examiner. Simply adjusting memory does not teach, suggest or disclose "anti-Hebbian learning". Anti-Hebbian learning is a much more sophisticated process relating to correlations of pre- and post-synaptic activity.

To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "anti-Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of a <u>learning</u> mechanism. Appellant's <u>anti-Hebbian</u> learning mechanism must operate in a very specific manner in order to provide for <u>anti-Hebbian</u> learning. In order to understand what anti-Hebbian learning is, the Appellant believes it would be helpful for the Examiner to refer to the brief overview of Hebbian learning provided early. Hebbian theory and Hebbian learning is simply not anticipated inherently or otherwise anywhere within Thakoor. In general, Hebbian learning can thus be implemented in neural networks as a technique for modifying connection based on correlations in pre- and post-synaptic activity. Anti-Hebbian learning is essentially the opposite of Hebbian-based learning techniques. In anti-

Hebbian learning, the connections are weakened when connections and/or neurons are correlated in activity, and strengthened when pre- and post-synaptic activity is anti-correlated. Such anti-Hebbian learning is not suggested, disclosed or taught by Thakoor no page 3133, left column, lines 1-14 cited by the Examiner.

Based on a review of Thakoor and a basic understanding of Hebbian learning it is very clear that Thakoor does not provide for any teaching, suggestion or disclosure of anti-Hebbian learning. Additionally, it is very clear that Thakoor does not inherently anticipate anti-Hebbian learning, and thus the Hebbian learning mechanism provided by Appellant's invention. The Examiner has not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of anti-Hebbian plasticity <u>necessarily</u> flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory"

Thus, from a prima facie anticipation standpoint, Thakoor provides no disclosure of <u>anti-Hebbian</u> learning (or <u>Hebbian</u> learning for that matter). From an inherency-based anticipation standpoint, anti-Hebbian learning clearly does not necessarily flow form the teachings of Thakoor and thus Thakoor does not inherently anticipate the <u>anti-Hebbian</u> plasticity of Appellant's invention.

Regarding claim 6, the Examiner argued that Thakoor teaches the system of claim 1 wherein said learning mechanism utilizes voltage gradient dependencies associated with the physical neural network to implement anti-Hebbian learning within the physical neural network (the Examiner cited Figure 2 of Thakoor in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 6. Figure 2 of Thakoor does not provide for any teaching of <u>anti-Hebbian plasticity</u>. The Examiner has not identified how voltage gradient dependencies bring about anti-Hebbian plasticity, particularly when there is not even a mention of plasticity or anti-Hebbian plasticity anywhere within Thakoor.

Instead, Figure 2 of Thakoor only illustrates a graph of resistance versus time (in minutes), and programming characteristics based on resistance versus time with

respect to various voltages. This is not anti-Hebbian plasticity as taught by Appellant's claim 6.

Regarding claim 7, the Examiner argued that Thakoor teaches the system of claim 1 wherein said learning mechanism utilizes pre-synaptic and post-synaptic frequencies to provide anti-Hebbian learning within said physical neural network (the Examiner cited page 3132, left column, lines 24-41; and page 3133, left column, lines 1-14 in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 7. Also, the arguments that the Appellant presented above earlier with respect to age 3132, left column, lines 24-41; and page 3133, left column, lines 1-14 apply equally against claim 7. Page 3132, left column, lines 24-41 generally describes the reprogrammable resistor with memory, i.e., a memistor. There is no teaching or disclosure at page 3132, left column, lines 24-41 of pre-synaptic frequencies or post-synaptic frequencies. There is also no teaching or disclosure at page 3132, left column, lines 24-41 of anti-Hebbian learning. The Examiner has merely cited page 3132, left column 24-41 of Thakoor without specifically pointing out which features here anticipate pre-synaptic and post-synaptic frequencies and anti-Hebbian learning and how such pre-synaptic and post-synaptic frequencies provide for anti-Hebbian learning.

With regard to inherency-based anticipation, the Appellant notes that it is incumbent upon the Examiner to point to the page and line of the prior art that justifies the rejection based on an inherency theory. The Examiner must not leave the Appellant to guess at the basis of the inherency rejection. Additionally, the fact that a certain result or characteristic <u>may</u> occur or be present in the prior art is not sufficient to establish the inherency of that result or characteristic. In this case, the Appellant is left guessing as to which features of page 3132, left column 24-41 of Thakoor constitute pre-synaptic and post-synaptic frequencies and anti-Hebbian learning. Additionally, simply because page 3132, left column 24-41 of Thakoor mentions neural network architectures and neurons and synapses does is not sufficient to establish inherency with respect to pre-synaptic and post-synaptic frequencies and anti-Hebbian learning.

Regarding page 3133, left column, lines 1-14 cited by the Examiner, again the Appellant notes that is clearly no teaching or disclosure here of pre-synaptic frequencies or post-synaptic frequencies or anti-Hebbian learning. The Examiner has merely cited page 3133, left column, lines 1-14 of Thakoor without specifically pointing out which features here anticipate pre-synaptic and post-synaptic frequencies and anti-Hebbian learning and how such pre-synaptic and post-synaptic frequencies provide for anti-Hebbian learning.

With regard to inherency-based anticipation, the Appellant reminds the Examiner that it is incumbent upon the Examiner to point to the page and line of the prior art that justifies the rejection based on an inherency theory. The Examiner must not leave the Appellant to guess at the basis of the inherency rejection. Additionally, the fact that a certain result or characteristic may occur or be present in the prior art is not sufficient to establish the inherency of that result or characteristic. In this case, the Appellant is left guessing as to which features of 3133, left column, lines 1-14 of Thakoor constitute pre-synaptic and post-synaptic frequencies and anti-Hebbian learning.

Regarding claim 9, the Examiner argued that Thakoor teaches the system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanowires (the Examiner cited page 3133, left column, lines 4-5 of Thakoor in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 9. Page 3133, left column, lines 4-5 of Thakoor does not teach, disclose or suggest "nanowires" as taught by Appellant's claim 9. Instead, page 3133, left column, lines 4-5 of Thakoor indicates only that "the rate of formation of $H_xWO_3$ depends primarily on the control voltage". $H_xWO_3$ is a chemical compound used as an ion insertion material, but not a nanowire as taught by Appellant's claim 9.

In order to understand what a nanowire is, the Appellant believes it would be helpful for the Examiner to review the information about nanowires freely available at the following web site:

***http://en.wikipedia.org/wiki/Nanowire***

The first thing to appreciate about a nanowire is that it is a wire. The $H_xWO_3$ of Thakoor is not a wire. A nanowire is a wire of dimensions of the order of a nanometer ($10^{-9}$ meters). Alternatively, nanowires can be defined as structures that have a lateral size constrained to tens of nanometers or less and an unconstrained longitudinal size. At these scales, quantum mechanical effects are important — hence such wires are also known as "quantum wires". Many different types of nanowires exist, including metallic (e.g., Ni, Pt, Au), semiconducting (e.g., InP, Si, GaN, etc.), and insulating (e.g., $SiO_2$,$TiO_2$). Molecular nanowires are composed of repeating molecular units either organic (e.g. DNA) or inorganic (e.g. $Mo_6S_{9-x}I_x$).

Typical nanowires exhibit aspect ratios (the ratio between length to width) of 1000 or more, but this value may vary. As such they are often referred to as 1-Dimensional materials. Nanowires have many interesting properties that are not seen in bulk or 3-D materials. This is because electrons in nanowires are quantum confined laterally and thus occupy energy levels that are different from the traditional continuum of energy levels or bands found in bulk materials. Peculiar features of this quantum confinement exhibited by certain nanowires such as carbon nanotubes manifest themselves in discrete values of the electrical conductance. Such discrete values arise from a quantum mechanical restraint on the number of electrons that can travel through the wire at the nanometer scale. These discrete values are often referred to as the quantum of conductance and are integer values of $\frac{2e^2}{h} \approx 12.9\ \mathrm{k}\Omega^{-1}$. They are inverse of the well-known resistance unit $h/e^2$, which is roughly equal to 25812.8 ohms, and referred to as the von Klitzing constant $R_K$ (after Klaus von Klitzing, the discoverer of exact quantization). Since 1990, a fixed conventional value $R_{K-90}$ is accepted.

Examples of nanowires include inorganic molecular nanowires ($Mo_6S_{9-x}I_x$), which have a diameter of 0.9 nm, and can be hundreds of micrometers long. Other important examples are based on semiconductors such as InP, Si, GaN, etc., dielectrics (e.g. $SiO_2$,$TiO_2$), or metals (e.g. Ni, Pt).

The $H_xWO_3$ material of Thakoor is not a nanowire as known in the art. FIG. 1 of Thakoor and page 3132-3133 of Thakoor makes it clear that the $WO_3$ of Thakoor is not a wire but merely a layer of the memistor device. The $H_xWO_3$ compound of Thakoor is the result of a chemical reaction wherein an influx of H+ ions react with the $WO_3$ layer to form the $H_xWO_3$ compound. On the contrary, the nanowires of Appellant's invention are disposed in a dielectric medium and do not occur as a result of a chemical reaction. Rather, they are used in a process, which is mechanical, not chemical. Appellant's nanowires are pre-disposed in a dielectric medium rather than as a result of the chemical reaction as part of the process of forming the Thakoor memistor device. It is also significant to note that $H_xWO_3$ is tungstic acid (see page 3133, left column, line 4 of Thakoor). Mixing tungstic acid with Appellant's dielectric medium does not make sense because the acid would destroy the viability of Appellant's dielectric medium.

The $H_xWO_3$ compound of Thakoor simply does not inherently or directly anticipate the nanowires of Appellant's invention. The Examiner has simply not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of a nanowire flows from the teachings from the $H_xWO_3$ compound of Thakoor. Thus, the Appellant submits that the $H_xWO_3$ compound of Thakoor does not anticipate the nanowires of Appellant's invention.

Regarding claim 10, the Examiner argued that Thakoor teaches the system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanoparticles (the Examiner cited page 3133, left column, lines 4-5 in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 10. Page 3133, left column, lines 4-5 of Thakoor does not teach, disclose or suggest "nanoparticles" as taught by Appellant's claim 10. Instead, page 3133, left column, lines 4-5 of Thakoor indicates only that "the rate of formation of $H_xWO_3$ depends primarily on the control voltage". $H_xWO_3$ is a chemical compound, but not a nanoparticle as taught by Appellant's claim 10. There is no disclosure here of nanoparticles as taught by Appellant's claim 10. Based on the foregoing, the Appellant submits that the

rejection to claim 10 has been traversed. The Appellant respectfully requests withdrawal of the rejection to claim 10 under 35 U.S.C. 102.

Regarding claim 11, the Examiner argued that Thakoor teaches a system, comprising:

a physical neural network configured utilizing nanotechnology (the Examiner cited "title" in support of this argument), wherein said physical neural network comprises a plurality of nanoconductors suspended and free to move about in a dielectric medium (citing page 3132, right column, lines 10-12; and page 3133, right column, lines 3-5) which form neural connections between pre-synaptic and post-synaptic components of said physical neural network (the Examiner cited page 3132, left column, lines 24-41 of Thakoor in support of this argument; and

a learning mechanism for applying Hebbian learning to said physical neural network wherein said learning mechanism utilizes a voltage gradient or pre-synaptic and post-synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within said physical neural network (the Examiner cited page 3133, left column, lines 1-14 of Thakoor in support of this argument).

The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claims 1, 6, 7 apply equally to the rejection to claim 11. In the interest of brevity, the Appellant will not repeat these arguments. The Appellant notes again, based on the arguments presented earlier, that there is no anticipation, inherent or otherwise, of the use of Appellant's dielectric medium, nanoconductors (e.g., DNA, nanowires, nanotubes, etc) free to move about in the dielectric medium, nanotechnology, physical neural network, pre-synaptic and post-synaptic components, Hebbian learning, a learning mechanism, the use of a voltage gradient or pre-synaptic and post-synaptic frequencies to implement Hebbian/anti-Hebbian plasticity and so forth.

Regarding claim 13, the Examiner argued that Thakoor teaches the system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanowires (the Examiner cited page 3133, left column, lines 4-5 in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 11 apply equally against the rejection to claim 13. The Appellant also

submits that the arguments presented above against the rejection to claims 1 and 9 apply equally to the rejection to claim 13. As such, Thakoor does not anticipate, inherently or otherwise, the nanowires of Appellant's invention. Based on the foregoing, the Appellant submits that the rejection to claim 13 has been traversed. The Appellant respectfully requests withdrawal of the rejection to claim 13 under 35 U.S.C. 102.

Regarding claim 14, the Examiner argued that Thakoor teaches the system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanoparticles (the Examiner cited page 3133, left column, lines 4-5 in support of this argument). The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claim 11 apply equally against the rejection to claim 14. The Appellant also submits that the arguments presented above against the rejection to claims 1 and 10 apply equally against the rejection to claim 14. As such, Thakoor does not anticipate, inherently or otherwise, the nanoparticles of Appellant's invention. Based on the foregoing, the Appellant submits that the rejection to claim 14 has been traversed. The Appellant respectfully requests withdrawal of the rejection to claim 14 under 35 U.S.C. 102. Based on the foregoing, the Appellant submits that the rejection to claim 14 has been traversed. The Appellant respectfully requests withdrawal of the rejection to claim 14 under 35 U.S.C. 102.

Regarding claim 15, the Examiner argued that Thakoor teaches the system of claim 11 wherein said dielectric medium comprises a dielectric liquid. The Appellant cited page 3132, right column, lines 10-12; and page 3133, right column, lines 3-5 in support of this argument.

Page 3132, right column, lines 10-12 indicates that "a thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serving as a hydrogen ion source is deposited by reactive magnetron sputtering".

Page 3133, right column, lines 3-5 indicates that "...since the $Cr_2O_3$ film serves as a source of H+ ions, its ability to absorb and retain water is crucial to the device operation".

The Examiner is therefore asserting that chromium trioxide ($Cr_2O_3$) is used as a dielectric liquid. This is simply not the case. Again, as indicated previously, the

$Cr_2O_3$ of Thakoor constitutes a hydrogen ion source and not a dielectric liquid. Chromium trioxide ($Cr_2O_3$) is also a solid and not a liquid. (Recall that the device of memistor is a solid-state device, i.e., see title of Thakoor, and not a liquid-state device). In order to appreciate why the chromium trioxide of Thakoor is not used as a dielectric, the Appellant believes it would be helpful to discuss what a dielectric is and is not and also analyze some of the properties inherent to chromium trioxide.

A dielectric is a material that tends to concentrate an applied electric field (e-field) within itself. As the dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. The chromium trioxide ($Cr_2O_3$) of Thakoor is hygroscopic as Thakoor clearly states. A "hygroscopic" is something that attracts water. However, as indicated previously and is well known in the chemical arts, $Cr_2O_3$ is a solid. Thakoor also indicates that that the memistor of Thakoor is a "solid-state" device. See, for example, the title of Thakoor: "Solid-State thin-film memistor, etc." Additionally, simply because something attracts water does not make it a liquid such as the dielectric liquid taught by Appellant's invention. $Cr_2O_3$ in its hygroscopic form can attract water, but $Cr_2O_3$ remains a solid.

A dielectric, on the other hand, does not "attract" water. Also, chromium trioxide ($Cr_2O_3$) does not tend to concentrate an applied electric field within itself and does not interact with the applied electric field so that charges are redistributed within atoms or molecules of the $Cr_2O_3$ compound. It is also important to note that chromium trioxide, when combined with water, forms a strong acid, also known as chromic acid. An acid would tend to corrode Appellant's nanoconductors such as DNA, carbon nanotubes, gold nanowires, etc and thus it would not make sense to incorporate chromium trioxide into a device that utilizes such nanoconductors because the nanoconductors, when in contact with the chromium trioxide will become damaged.

Additionally, it is important to note that use of H+ ions and the thin film of hygroscopic chromium trioxide in order to achieve the memistor of Thakoor is electrolytic in nature. Thakoor clearly states that the thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serves as a hydrogen ion source (see Page 3132,

paragraph under heading "Experimental Details" of Thakoor). The Thakoor device is thus based on an electrolytic configuration, that is, the use of an electrolyte and not a dielectric. Thakoor, for examples, at page 3133, second column, third paragraph, specifically refers to the use of an electrolyte. The memistor of Thakoor is based on the use of the electrochemical process of electrolysis, which is the production of chemical changes by the passage of current through an <u>electrolyte</u> (not a dielectric).

An example of such an electrochemical process is described in the "Introduction" section of Thakoor, Page 3132, Column 1, lines 34 to Column 2, line 2, where Thakoor states that "...in this paper, we report on the operational characteristics and application potential of a solid-state 'memistor," an analog memory device based on the electrochemical ion transport to/from tungsten oxide in a thin-films structure. The three-terminal devices utilizes a reversible transfer of metal (hydrogen) ions in tungsten oxide..." The use of <u>electrolytes</u> is taught, for example on page 3133, column 1, lines 24-26 of Thakoor where Thakoor refers to "$WO_3$/<u>electrolyte</u> display". The memistor of Thakoor is based on the production of chemical changes by the passage of current through an <u>electrolyte</u>.

An electrolyte is a substance containing free <u>ions</u> which behaves as an electrically conductive medium. Electrolytes are generally composed of ions in a solution of some sort. The use of free ions for a substance that behaves as electrically conductive medium, differs from that of the use of a <u>dielectric</u>, which tends to concentrate an applied electric field within itself. This is a fundamental and key difference between Thakoor and Appellant's invention. Unlike an electrolyte, such as that employed by Thakoor, as a <u>dielectric</u> interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the <u>dielectric</u> material. This is <u>not</u> true of electrolytic materials such as that used to create the memistor of Thakoor. This also not true of the hygroscopic chromium trioxide ($Cr_2O_3$) material of Thakoor.

Thus, to summarize, Thakoor's device is based on the use of electrolytes, whereas Appellant's device is based on the use of a dielectric. Also, Appellant's claim 15 specifically refers to the use of a "dielectric liquid". Again, $Cr_2O_3$ is a solid.

Per the requirements of claim 15, Appellant's nanoconductors (e.g., nanotubes, nanowires, DNA, etc) are disposed in the dielectric liquid and free to move about in the dielectric liquid solution. Such nanoconductors could not possibly be free to move about in a solid such as $Cr_2O_3$. This is physically impossible.

Based on the foregoing, it can be appreciated from a strict prima facie anticipation standpoint, Thakoor does not disclose the dielectric liquid taught by Appellant's invention. From an inherency-based anticipation standpoint, it is also clear that Thakoor does not inherently anticipate Appellant's dielectric liquid. That is, based on the requirements of establishing inherency as a basis for anticipation, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor does not inherently anticipate the dielectric liquid of Appellant's invention, because in relying upon the theory of inherency, the Examiner has not provided a basis in fact and/or technical reasoning to reasonably supporting the determination that the allegedly inherent characteristic of the use of a dielectric liquid in which Appellant's nanoconductors are free to move about <u>necessarily</u> flows from the teachings of the Thakoor reference. One skilled in the art would clearly not see the chromium trioxide of Thakoor as teaching the dielectric liquid of Appellant's invention. The evidence provided above proves the opposite.

Regarding claim 16, the Examiner argued that Thakoor teaches the system of claim 15 wherein said plurality of nanoconductors form physical neural connections when said dielectric medium is exposed an electric field, such that said physical neural connections can be strengthened or weakened depending upon a strengthening or weakening of said electric field or an alteration of a frequency thereof (the Examiner cited page 3133, left column, lines 1-14 in support of this argument). The Appellant respectfully disagrees with this assessment and notes that all of the arguments presented above against the rejection to claim 15 apply equally against the rejection to claim 16.

Page 3133, left column, lines 1-14 of Thakoor does not disclose <u>all</u> of the following claim limitations of Appellant's claim 16: <u>nanoconductors</u> that form <u>physical neural connections</u>, the <u>dielectric medium</u> <u>exposed</u> <u>to</u> an <u>electric field</u>, and physical neural connections that can be <u>strengthened</u> or <u>weakened</u> depending upon a strengthening or weakening of said <u>electric field</u> or an alteration of a <u>frequency</u>

thereof. Instead, page 3133, left column, lines 1-14 of Thakoor refers generally to "an electric field that drives $H^+$ ions from $Cr_2O_3$ toward the cathodic $WO_3$" and to the "injection of H+ ions (protons)" and so forth, but does not provide for a disclosure and/or teaching of <u>nanoconductors</u> disposed within a <u>dielectric medium</u> used for creating a physical neural network. There is also no disclosure here of <u>neural</u> connections and the strengthening or weakening of such <u>neural</u> connections. As indicated earlier, Thakoor also does not disclose, suggest and/or teach nanoconductors as taught by Appellant's invention. Based on the foregoing, the Appellant submits that the rejection to claim 16 has been traversed. The Appellant respectfully requests withdrawal of the rejection to claim 16 under 35 U.S.C. 102.

Regarding claim 17, the Examiner argued that Thakoor teaches a system, comprising:

a plurality of molecular conductors disposed within a dielectric medium comprising a dielectric solvent or a dielectric solution (the Examiner cited page 3133, left column, lines 1-14 in support of this argument);

at least one input electrode in contact with said dielectric medium (the Examiner cited page 3133, left column, lines 1-14 in support of this argument); and

at least one output electrode in contact with said dielectric medium, wherein said plurality of molecular conductors form physical neural connections when said dielectric medium is exposed an electric field across said at least one input electrode and said at least one output electrode, such that said physical neural connections can be strengthened or weakened depending upon a strengthening or weakening of said electric field or an alteration of a frequency thereof (the Examiner cited page 3132, left column, lines 24-41; and page 3133, left column, lines 1-14 in support of this argument).

The Appellant respectfully disagrees with this assessment and submits that the arguments presented above by the Appellant against the rejection to claims 1-16 apply equally against the rejection to claim 17. Page 3133, left column, lines 1-14 of Thakoor does not disclose the use of a "dielectric medium comprising a dielectric solvent or a dielectric solution" as taught by Appellant's amended clam 17, and in which nanoconductors (e.g., nanotubes, nanowires, DNA, etc.) are free to move about in the dielectric medium. As indicated previously, Thakoor simply does

not provide for a teaching, disclosure or suggestion of the use of dielectric in which nanoconductors such as nanowires, nanotubes, DNA, etc are disposed and free to move about in order to form neural network connections.

Regarding the chromium trioxide of Thakoor, which the Examiner argues is used as a dielectric medium, the Appellant notes that one of the claim limitations of Appellant's claim 17 is "at least one output electrode in contact with the dielectric medium". FIG. 1 of Thakoor indicates that the chromium trioxide of Thakoor (i.e., the H+ ion source of Thakoor) is not in contact with at least one output electrode but is instead positioned between SiO layers. The electrodes of Thakoor are actually disposed well below the chromium trioxide layer of Thakoor. Thus, the chromium trioxide layer of Thakoor is not in contact with an output electrode. Of course, as explained previously, the chromium trioxide of Thakoor is not a dielectric. Also, keep in mind that the memistor device of Thakoor is a three-terminal device and not a two-terminal device such as that of Appellant's invention, which is a significant difference between the two inventions. Additionally, as indicated previously the hygroscopic chromium trioxide attracts water and when combined with water can form an acid that is highly corrosive and which would damage Appellant's nanoconductors.

Additionally, on page 3132, left column, lines 24-41 and page 3133, left column, lines 1-14 there is no teaching, disclosure and/or suggestion of "exposing an electric field" across the dielectric medium in order to strengthen or weaken neural connections based on the strengthening or weakening of the electric field or the alternation of a frequency thereof. Again, 3132, left column, lines 24-41, refers only to the reprogrammable resistor with memory (memistor) but provides no hint of a dielectric medium or the strengthening/weakening of neural connections. Page 3133, left column, lines 1-14 also does not provide any hint or disclosure of a dielectric medium or the strengthening/weakening of neural connections.

Regarding claim 18, the Examiner argued that Thakoor teaches the system of claim 17 further comprising a physical neural network comprising said plurality of molecular conductors disposed within a dielectric medium comprising a dielectric solvent or a dielectric solution (citing page 3132, right column, lines 10-12), said at least one input electrode in contact with said dielectric medium, and said at least

one output electrode in contact with said dielectric medium (the Examiner cited page 3133, left column, lines 1-14 of Thakoor in support of this argument). The Appellant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 17 apply equally against the rejection to claim 18.

Page 3132, right column, lines 10-12 indicates that "a thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serving as a hydrogen ion source is deposited by reactive magnetron sputtering".

Page 3133, left column, lines 1-14, states the following:

"...electrodes, the electric field drive H+ ions from the Cr2O3 toward the cathode WO3. The injection of H+ ions (protons) into the WO3 (insulating) layer results in the formation of conducting HxWO3 (tungstic acid). The rate of formation of HxWO3 depends primarily on the control voltage. The above process can be reversed by an application of a negative control voltage (with respect to the read electrodes). In the reverse process, anodic dissociation of HxWO3 proceeds with the liberation of hydrogen. The rate of dissociation can also e varied with the magnitude of the control voltage....the reistance of the devices was measured with the control electrode at ground potential and a small voltage (~ 100 milivolts) applied across the read electrodes".

The Examiner is therefore asserting that chromium trioxide ($Cr_2O_3$) is used as a dielectric medium comprising a dielectric solvent or a dielectric solution. This is simply not the case. The $Cr_2O_3$ of Thakoor constitutes a hydrogen ion source and is not used as a dielectric medium comprising a dielectric solvent or a dielectric solution. In order to appreciate why the chromium trioxide of Thakoor is not used as a dielectric solvent or a dielectric solution, the Appellant believes it would be helpful to discuss what a dielectric is and is not and also analyze some of the properties inherent to chromium trioxide.

A dielectric is a material that tends to concentrate an applied electric field (e-field) within itself. As the dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. The chromium trioxide ($Cr_2O_3$) of Thakoor is hygroscopic as

Thakoor clearly states. A "hygroscopic" is something that attracts water. $Cr_2O_3$ is also a solid. A dielectric does not "attract" water. In fact, if a dielectric did attract water the water itself would damage Appellant's dielectric medium and plurality of nanoconductors disposed in the dielectric medium, so it would not make sense to use a "hygroscopic" material such as that of Thakoor. Chromium trioxide ($Cr_2O_3$) does not tend to concentrate an applied electric field within itself and does not interact with the applied electric field so that charges are redistributed within atoms or molecules of the dielectric. It is also important to note that as indicated previously, chromium trioxide when in contact with water (which is necessary for Thakoor to produce H+ ions) creates an acid, also known as chromic acid. An acid will corrode Appellant's nanoconductors such as DNA, carbon nanotubes, gold nanowires, etc and thus it would not make sense to incorporate chromium trioxide into a device that utilizes such nanoconductors because the nanoconductors, when in contact with the chromium trioxide will become damaged.

Additionally, it is important to note that use of H+ ions and the thin film of hygroscopic chromium trioxide in order to achieve the memistor of Thakoor is electrolytic in nature. Thakoor clearly states that the thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serves as a hydrogen ion source (see Page 3132, paragraph under heading "Experimental Details" of Thakoor). There is no evidence from Thakoor that the chromium trioxide is used as a dielectric medium in which nanoconductors (e.g., nanotubes, nanowires, DNA, etc) are free to move about in the dielectric medium. The Thakoor device is based on an electrolytic configuration, that is, the use of an electrolyte and not on the use of a dielectric to perform a particular process. Thakoor, for examples, at page 3133, second column, third paragraph, specifically refers to the use of an electrolyte. The memistor of Thakoor is based on the use of the electrochemical process of electrolysis, which is the production of chemical changes by the passage of current through an <u>electrolyte</u> (not a dielectric).

An example of such an electrochemical process is described in the "Introduction" section of Thakoor, Page 3132, Column 1, lines 34 to Column 2, line 2, where Thakoor states that "...in this paper, we report on the operational characteristics and application potential of a solid-state 'memistor," an analog

memory device based on the electrochemical ion transport to/from tungsten oxide in a thin-films structure. The three-terminal devices utilizes a reversible transfer of metal (hydrogen) ions in tungsten oxide..." The use of electrolytes is taught, for example on page 3133, column 1, lines 24-26 of Thakoor where Thakoor refers to "$WO_3$/electrolyte display". The memistor of Thakoor is based on the production of chemical changes by the passage of current through an electrolyte.

An electrolyte is a substance containing free ions which behaves as an electrically conductive medium. Electrolytes are generally composed of ions in a solution of some sort. The use of free ions for a substance that behaves as electrically conductive medium, differs from that of a dielectric, which tends to concentrate an applied electric field within itself. This is a fundamental and key difference between Thakoor and Appellant's invention. Unlike an electrolyte, such as that employed by Thakoor, as a dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. This is not true of electrolytic materials such as that used to create the memistor of Thakoor.

Thus, to summarize, Thakoor's device is based on the use of electrolytes, whereas Appellant's device is based on the use of a dielectric. Additionally, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor is not a dielectric solvent or a dielectric solution and also tends to attract water, which will damage the dielectric configuration of Appellant's invention and when in acid form, will corrode Appellant's nanoconductors.

Based on the foregoing, it can be appreciated from a strict prima facie anticipation standpoint, Thakoor does not disclose the dielectric medium taught by Appellant's invention. From an inherency-based anticipation standpoint, it is also clear that Thakoor does not inherently anticipate the use of Appellant's dielectric medium comprising a dielectric solvent or a dielectric solution and one in which nanoconductors (as taught by Appellant) are disposed and free to move about. That is, based on the requirements of establishing inherency as a basis for anticipation, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor does not inherently anticipate the use of a dielectric medium (comprising a dielectric solvent

or a dielectric solution) in which nanoconductors (e.g., DNA, nanowires, nanotubes) are to free to move about, because in relying upon the theory of inherency, the Examiner has not provided a basis in fact and/or technical reasoning to reasonably supporting the determination that the allegedly inherent characteristic of the use of a dielectric solvent or a dielectric solution as taught by Appellant's invention necessarily flows from the teachings of the Thakoor reference. One skilled in the art would clearly not see the chromium trioxide of Thakoor as teaching the use of a dielectric solvent or a dielectric solution of Appellant's invention. The evidence provided above proves the opposite.

Regarding claim 19, the Examiner argued that Thakoor teaches the system of claim 18 further comprising a learning mechanism for applying Hebbian learning to said physical neural network wherein said learning mechanism utilizes a voltage gradient or pre-synaptic and post-synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within said physical neural network (the Examiner cited Figure 2 of Thakoor in support of this argument). The Appellant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 18 apply equally against the rejection to claim 19.

The Appellant also submits that the arguments presented earlier by the Appellant regarding Hebbian and/or anti-Hebbian learning and/or plasticity apply equally against the rejection to claim 19. As such, Thakoor and particularly FIG. 2 of Thakoor do not anticipate, directly or inherently, Hebbian and anti-Hebbian plasticity and use of a voltage gradient or pre-synaptic or post-synaptic frequencies to implement Hebbian and anti-Hebbian plasticity.

Regarding claim 20, the Examiner argued that Thakoor teaches the system of claim 18 wherein said physical neural network is configured as an integrated circuit chip utilizing nanotechnology (the Examiner cited Figure 3 of Thakoor in support of this argument). The Appellant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 18 apply equally against the rejection to claim 20. The Appellant also submits that the arguments presented above against the rejection to claims 1-19 apply equally against the rejection to claim 20. Figure 3 of Thakoor does not illustrate an integrated circuit chip, but simply illustrates a circuit that can perform autonulling

utilizing a WO3 think film memistor. Figure 3 also provides for no teaching of nanotechnology.

As indicated previously, Thakoor is not a nanotechnology-based device and does not employ nanoconductors such as nanotubes, nanowires, DNA, etc. Again, the H+ ions of Thakoor are not nanoconductors as such nanoconductors are known in the art (i.e., see above arguments/explanations by Appellant regarding the H+ ions of Thakoor and what is meant by the term nanotechnology).

Based on the foregoing, the Appellants submit that the rejection to the claims belonging to GROUP I under 35 U.S.C. § 102(b) based on *Thakoor* fails to meet all the elements of a *prima facie* case of anticipation and a case of inherency-based anticipation. *Thakoor* does not disclose each all of the claim limitations of Appellant's claims 1-7, 9-11 and 13-20 as defined and supported by Appellants' specification. A person of ordinary skill in the field of the invention would see the above-identified differences between the claimed invention and *Thakoor*.

For the foregoing reasons, independent claims 1-7, 9-11 and 13-20 should have been allowed by the Examiner. Appellant now pray for reversal of the examiner and instruction to allow the rejected claims. Appellant therefore respectfully requests reversal of the rejection to the claims belonging to Group I.

## APPELLANT'S ARGUMENTS REGARDING ISSUE #2 - ARGUMENTS IN SUPPORT OF PATENTABILITY OF GROUP II CLAIMS:

### Claims 8 and 12 (Group II) are patentable over Thakoor in view of Srivastava.

In the Final Rejection dated November 2, 2006, Claims 8 and 12 were rejected by the Examiner under 35 U.S.C. 103(a) as being unpatentable over Thakoor as applied to claims 1-7, 9-11 and 13-20 above, and further in view of "Computational Nanotechnology with Carbon Nanotubes and Fullerenes," by Srivastava.

Claims 8 and 12 read as follows:

8. (Original) The system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanotubes.

12. (Original) The system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanotubes.

The Examiner argued that the Thakoor teaches a physical neural network configured utilizing nanotechnology wherein said physical neural network comprises a plurality of nanoconductors. The Office Action admitted that Thakoor fails to disclose that said plurality of nanoconductors includes nanoconductors comprising nanotubes.

The Examiner asserted that Srivastava teaches computational nanotechnology with carbon nanotubes and fullerenes and that it would have been obvious at the time the invention was made to a person having ordinary skill in the art to combine the physical neural network utilizing nanotechnology of Thakoor with the carbon nanotubes of Srivastava. The Examiner argued that the motivation for doing so would be to perform complex computing and switching applications in a single pass and also, the signals propagated, branched, and switched on such a network need not be restricted to the "electronic" regime (the Office Action cited page 52, left column, lines 3-11 of Srivastava in support of this argument).

The Appellant respectfully disagrees with this assessment and submits that the arguments presented above against the rejection to claims 1-7, 9-11 and 13-20 under 35 U.S.C. 102 apply equally against the rejection to claims 8 and 12 under 35 U.S.C. 103. Thus, as indicated earlier, the Thakoor reference does not anticipate (inherently or otherwise) all of the claim limitations of the claims from which claims 8 and 12 depend. Thakoor therefore cannot properly be combined with Srivastava as a basis for a rejection to claims 8 and 12 under 35 U.S.C. 103.

The Appellant submits that the rejection to claims 8 and 12 under 35 U.S.C. 103 fails under all three prongs of the prima facie obviousness test described above. First, there is no suggestion or motivation either in the references themselves or in the knowledge generally available to one of ordinary skill in the art, to modify the references or to combine the reference teaching as argued by the Examiner. The use of the electrolytic process and the hygroscopic chromium trioxide of Thakoor teaches away from any ability to combine the nanotubes of Srivastava with the solid chromium trioxide of Thakoor. This is so for two reasons. Appellant provides for a teaching of nanoconductors (e.g., nanotubes, nanowires, DNA, etc) that are disposed and free to move about in a dielectric medium. Because the memistor device is a solid-state device and the chromium trioxide of Thakoor is a solid, there is no hint, suggestion or teaching as to how the nanotubes of Srivastava would freely move about in the chromium trioxide of Thakoor, and hence no motivation for combining the references as argued by the Examiner.

Second, as indicated previously, the chromium trioxide of Thakoor is hygroscopic and attracts water in order function as a hydrogen ion source. When water is combined with chromium trioxide, this makes for a strong acid and thus one skilled in the art would not be motivated be either Thakoor or Srivastava to use the nanotubes of Srivastava with the Thakoor device because the nanotubes of Srivastava would be corroded by the resulting acid. Third, the presence of water would also damage the nanotubes of Srivastava. There is simply not a motivation for combining the references as argued by the Examiner because doing so would simply result in damage to the nanotubes of Srivastava.

Regarding the second prong of the aforementioned prima facie obviousness test, a review of Srivastava and Thakoor reveals that there is <u>not</u> a reasonable

expectation of success for combining the references as argued by the Examiner. First, combining the carbon nanotubes of Srivastava with Thakoor would mean somehow injecting or combining (which is not event hinted at in either reference how this would be accomplished) such nanotubes into or with the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor. The Appellant notes that chromium trioxide is a solid. How would such nanotubes be successfully combined with such a solid? Where is the suggestion in either Srivastava or Thakoor that such nanotubes could be combined with such a solid? The Appellant has looked for such a suggestion in the prior art references but cannot find it.

Combining nanotubes to freely move about in such a solid would be very difficult based on a reading of both the Srivastava and Thakoor references. Chromium trioxide is a dark-red, odorless flakes or powder. Thus, it is a solid. More importantly, chromium trioxide is an acid and is often referred to as chromic acid. Ethanol, for example, will ignite on contact with it. What happens when the nanotubes of Srivastava are combined with the chromic acid of Thakoor? The acid dissolves and breaks down the nanotubes of Srivastava and renders them useless. One skilled in the art would realize this.

Additionally, Srivastava does not provide for any teaching of neural networks nor any hint or suggestion of how the nanotubes or fullerenes described in the Srivastava could be adapted for use with a physical neural network as taught by Appellant's claims 8 and 12. Page 52, left column, lines 3-11 of Srivastava provides for no hint, suggestion, or teaching of a physical neural network as taught by Appellant's claims 8 and 12. Instead, page 52 left column, lines 3-11 merely refers to a "biological neural network" but does not indicate how a carbon nanotube could be adapted for use in the physical neural network taught by Appellant's claims 8 and 12. Additionally, as indicated above, Thakoor does not describe a physical neural network as taught by Appellant's claims 8 and 12. Thus, there is no motivation for combining Srivastava and Thakoor as argued by the Office Action to derive all of the claim limitations of Appellant's claims 8 and 12. Given the presence of the chromic acid in Thakoor, it would be highly unlikely that one skilled in the art would be motivated to combine the nanotubes of Srivastava with the chromic acid

in Thakoor because the chromic acid would likely severely damage the nanotubes of Srivastava and render them useless.

Additionally, both Thakoor and Srivastava fail to provide any hint, teaching or suggestion of the use of a dielectric medium as taught by Appellant's invention. As indicated previously, Thakoor provides for electrolytes and the use of chromic acid (i.e., chromium trioxide). Srivastava provides no hint of nanotubes disposed in a dielectric medium, or of the use of nanotubes in association with a dielectric and also a dielectric medium in which nanotubes are free to move about. The fact that nanotubes conduct electricity and that a dielectric is not a conductor of electricity would lead one skilled in the art to overlook any use of dielectrics with the nanotubes of Srivastava.

Regarding the third prong of the aforementioned prima facie obviousness test the Appellant submits that the rejection to claims 8 and 12 under 35 U.S.C. 103 also fails because there is no teaching or suggestion of <u>all</u> the claim limitations by the Srivastava and Thakoor references when combined as argued by the Examiner. In the interest of brevity the Appellant will not repeat all of the differences, but simply point out again that all of the arguments presented earlier against the rejection to the claims under 35 U.S.C. 102 apply equally against the rejection to claims 8 and 12 under 35 U.S.C. 103.

Based on the foregoing, the Appellants submit that the rejection to the claims belonging to GROUP II under 35 U.S.C. § 102(b) based on the combination of Thakoor/Srivastava fails to meet all the elements of a *prima facie* case of anticipation and a case of inherency-based anticipation. Thakoor/Srivastava does not disclose each all of the claim limitations of Appellant's claims 8 and 12 as defined and supported by Appellants' specification. A person of ordinary skill in the field of the invention would see the above-identified differences between the claimed invention and Thakoor/Srivastava.

For the foregoing reasons, claims 8 and 12 should have been allowed by the Examiner. Appellant now pray for reversal of the examiner and instruction to allow the rejected claims. Appellant therefore respectfully requests reversal of the rejection to the claims belonging to Group II.

## IX. Rebuttal to Examiner's Response to Arguments in Final Office Action

In the Final Rejection dated November 2, 2006, which is incorporated herein by reference, the Examiner indicated that the Appellant's arguments filed August 14, 2006 were considered but that the Examiner finds such arguments unpersuasive. The Appellant provides the following rebuttal to these arguments.

### Rejection of Claims 1-7, 9-11, and 13-20 under 35 U.S.C. 102

#### Argument 1

Regarding Argument 1 (identified by the Examiner in the Office Action), the Examiner admitted that the Appellant is correct concerning the case citations regarding anticipation. The Examiner asserted, however, that patent law is more comprehensive than Appellant recited. The Examiner indicated that she refuses to believe that Appellant is asserting that he has enumerated an exclusive list of laws that apply with respect to § 102 rejections. The Examiner again stated that "patent law is more comprehensive than that". The Examiner then proceeded to provide examples of laws and rules that come into play in such circumstances. The Examiner cited MPEP 2112 where anticipation may be shown by "inherency". The Examiner stated that in contrast, the Appellant seems to argued that all elements in a rejection must be express in the prior art.

The Examiner argued that this is not the case. The Examiner stated that inherency is a ground for anticipation as well. The Examiner asserted that by the omission of this law in Appellant's argument, the Appellant has shown that his selections of law are overly narrow and misleading as to what is required for anticipation. The Examiner also referred to MPEP 1212 as authority for "inherency" and cited case law in In re Napier and In re Grasselli.

In addition to inherency, the Examiner indicated that Examiners are required to read the claims in their "broadest interpretation" under MPEP 2111. The Examiner argued that this is another principle used in conjunction with 102 rejections that weighs against the Appellant's implication that all claim elements must be express in the prior art. The Examiner then stated that "not all engineers

use the same vocabularies for things, so one must interpret the disclosures to see if the prior art is within the 'broadest reasonable interpretation' of the claimed invention. (The Appellant reminds the Examiner that, of course, the claims must be interpreted in light of the specification).

The Examiner then stated that consequently, Appellant's recital of law are helpful, but exclusive of all other law that can and must be applied during examination. The Examiner further stated that she has applied her rejections while cognizant of all this law and asserted that the Appellant has not made a specific and cogent argument regarding the Examiner's application of law here. The Examiner then stated that Appellant's argument suggesting that claim limitations must be express in the prior art is unpersuasive and the rejections stand.

The Appellant respectfully disagrees with this analysis. First, the Appellant provided the prima facie anticipation test because the Examiner did not establish inherency as a basis for the anticipation rejection. That is, because the Examiner did not establish inherency based under the requirements of what constitutes inherency-based anticipation, the prima facie anticipation still applies and needs to be considered by the Examiner in all cases. The Examiner should not simply ignore prima facie anticipation and argue only "inherency". The theory of inherency as a basis for an anticipation rejection should only be used under limited circumstances. The Examiner should not simply ignore the fact that a prima facie case of anticipation was not established. The Examiner should keep in mind that although inherency can be a factor for determining anticipation, so should the prima facie anticipation test presented by the Appellant.

The principle of inherency-based anticipation is more comprehensive than the Examiner recited. Simply stating that something is inherent in the prior art as a basis for arguing anticipation does not make it so. There are a number of factors that must be considered when attempting to establish inherency as a basis for anticipation. Inherency should only be applied under very limited circumstances. That is, inherency permits in very limited circumstances, an invention to be anticipated by prior art that is lacking minor, well-known features in the claimed invention. If the "missing subject matter" is "inherent" or necessarily disclosed in

the prior art reference, then anticipation can exist. As stated by the Federal Circuit (see In re Sun USPQ2d 1451, 1453 (Fed. Cir. 1983)

> ...To serve as an anticipation when the reference is silent about the asserted inherent characteristic, such gap in the reference may be filled with recourse to intrinsic evidence. Such evidence must make clear that the missing descriptive matter is necessarily present in the thing described in the reference and that it would be so recognized by persons of ordinary skill.

In this regard, the CCPA has added that "'[i]nherency, however, may not be established by probabilities or possibilities. The mere fact that a certain thing may result from a given set of circumstances is not sufficient". See In re Oelrich, 666 F.2d 578, 581, 212 USPQ 323, 326 (C.C.P.A. 1981) (quoting Hansgrig v. Kemmer, 102 F.2d 212, 214, 40 USPQ 665, 667 (C.C.P.A. 1930). That is, the missing element or function must necessarily result from the prior art reference.

Additionally, when an Examiner's rejection relies on inherency, it is incumbent upon the Examiner to point to the page and line of the prior art that justifies the rejection based on an inherency theory. The Examiner must not leave the Appellant to guess at the basis of the inherency rejection.

The fact that a certain result or characteristic <u>may</u> occur or be present in the prior art is not sufficient to establish the inherency of that result or characteristic. *In re Rijckaert*, 9 F.3d 1531, 1534, 28 USPQ2d 1955, 1957 (Fed. Cir. 1993) (reversed rejection because inherency was based on what would result due to optimization of conditions, not what was necessarily present in the prior art); *In re Oelrich*, 666 F.2d 578, 581-82, 212 USPQ 323, 326 (CCPA 1981). "To establish inherency, the extrinsic evidence 'must make clear that the missing descriptive matter is necessarily present in the thing described in the reference, and that it would be so recognized by persons of ordinary skill. Inherency, however, may not be established by probabilities or possibilities. The mere fact that a certain thing may result from a given set of circumstances is not sufficient.' " *In re Robertson*, 169 F.3d 743, 745, 49 USPQ2d 1949, 1950-51 (Fed. Cir. 1999) (citations omitted).

"In relying upon the theory of inherency, the examiner must provide a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic <u>necessarily</u> flows from the teachings of the applied prior art." *Ex parte Levy,* 17 USPQ2d 1461, 1464 (Bd. Pat. App. & Inter. 1990) (emphasis in original).

**Argument 2**

Regarding Argument 2, the Examiner provided a statement that "Appellant is reminded that although the claims are interpreted in light of the specification, limitations from the specification are not read into the claims." The Examiner cited In re Van Geuns, F.2d 1181, 26 USPQ2d 1057 (Fed. Cir. 1993).

The Examiner asserted that in this argument, the Appellant admitted Thakoor teaches "synapse" and a "memistor device". The Examiner argued that in the broadest reasonable interpretation of this art, a memistor device is interpreted as a physical neural network and pre-synaptic and post-synaptic components are inherent in synapses.

This is not true. In the broadest interpretation of the memistor of Thakoor, the memistor is only a memory unit and not a physical neural network or a synapse. Thakoor only indicates that the electrochemical analog memory effects of the memistor device "...in solid state devices are potentially useful in electronic neural networks for adaptive learning and optimization applications" (see page 3135, second column, lines 1-8. In other words, the memistor is useful for use in a physical neural network but in and of itself is <u>not</u> a physical neural network or a synapse. The memistor is merely one of many devices/components that could be adapted for use with a neural network. A resistor is a device that finds usefulness and that can be adapted for use in a neural network. This does not mean that the resistor is a neural network or a synapse. A transistor is a device that is useful in electronic neural networks but also is not a neural network or a synapse. Such devices are in and of themselves not neural networks. By attempting to equate the memistor with a physical neural network, the Examiner is making an incorrect comparison to a device that is fundamentally different from a physical neural network. Also, making this comparison is a bit like saying that a brick house is equal to a brick. A more appropriate comparison for a memistor would be devices such as transistors or resistors that complement the use of a neuron or other physical neural network components.

Thakoor at page 3132, left column, lines 34-41 defines a memistor as a reprogrammable resistor with memory and as an analog memory device. Thus, in

its broadest sense, the memistor of Thakoor does not teach a synapse or neural network but merely a memory unit that has programmable and memory capabilities. In its broadest sense, the memistor, which is the focus of the Thakoor reference, is simply a memory component and therefore in the broadest and reasonable interpretation of the art can only be interpreted as a memory device. Simply because the memistor of Thakoor can be adapted for use with a neural network does not mean that the memistor, which lies at the heart of the Thakoor reference, can be interpreted as constituting a neural network or a synapse.

It is also important to understand that the memistor of Thakoor is a three-terminal device and Appellant's invention is a two-terminal device. See, for example, FIG. 1 of Thakoor, which clearly shows a gate and two electrodes, thereby constituting a three-terminal configuration. The difference between a three-terminal device and a two-terminal device is significant in building large adaptive systems. In order to assist the Examiner in appreciating this difference, we provide the following discussion, which illustrates how the two-terminal device of Appellant's invention is adaptive, whereas the three-terminal device of Thakoor is not. Imagine two electrical devices - device 1 and device 2. Device 1 is composed of three-terminals, which we will call terminals A, B, C. The conductance between terminal A and C is a function of the voltage of terminal B. In other words, by applying a certain voltage to terminal B, we may increase the conductance between terminals A and C. By applying an opposite voltage, we may weaken the conductance between terminals A and C. Now, picture the second device, device 2, which only has two terminals, which we will refer to as A and C. The conductance between terminals A and C of device 2 is a function of the accumulation of voltage over time between terminals A and C. Now, to make clear how these two devices are used, we can say the following: for device 1, the conductance between terminals A and C is a function of what we <u>do</u> to terminal B; for device 2, the conductance between terminals A and C is a function of how we <u>use</u> terminals A and C. Device 2 implies <u>adaptability</u> whereas device 1 implies <u>programmability</u>. For example, the programmable nature of the Thakoor memistor is clearly illustrated by FIG. 2 of Thakoor, which plots the resistance as a function of the programming voltage.

To further illustrate the profound difference between programmability and adaptability, let us consider how one might make the Thakoor device adaptive according to Hebbian plasticity (i.e., Hebbian plasticity is not taught by Thakoor). Signals are represented as voltages. Hebbian plasticity is a rule for modifying the conductance of a synapse based on the accumulation of correlations between the pre- and post-synaptic electrodes. In order to modify the conductance of the Thakoor device, it would be necessary to modulate the voltage on the gate electrode of the Thakoor resistor. In other words, the gate programming voltage must be the result of a program that takes as its input the pre- and post-synaptic electrode voltages and provides as its output, the correct programming voltage. Of course, this program (i.e., circuit) is not inherent within the device of Thakoor but must be added by a designer to control (i.e., "program") the device. It is apparent how this device can be seen as only a memory element and not as an adaptive synapse because the adaptive program which is required to implement Hebbian plasticity is not present anywhere in the Thakoor memistor device.

Now consider the Appellant's device. The force felt by nanoparticles in the dielectric medium is a function of the voltage across the pre- and post-synaptic electrodes. The greater the force felt by the nanoparticles, the more nanoparticles/nanoconductors will be attracted to the connection gap. The more particles that are attracted to the connection gap, the stronger the connection becomes. One can clearly see how the conductance of the connection is a function of the voltages across the electrodes, which is the basis of plasticity and is what makes this synapse adaptive rather than programmable.

The Examiner further argued that as far as Appellant's claim for "nanoconductors" is concerned, the prior art anticipates this feature with H+ ions, which the Examiner argued are clearly measurable and verifiable to be on the nanometer scale. The Examiner asserted that the Appellant has not brought evidence to provide that H+ ions are not on the nanometer scale as the Examiner asserts.

The Examiner argued that the "nanoconductors" in Thakoor are "H+ ions" (or "H+ ions" as the prior art calls them). The Examiner argued that they are suspended in a "thin film of hygroscopic chromium trioxide" as the prior art calls

them. The Examiner asserted that this is the "dielectric medium" of Appellant's invention.

The Appellant respectfully disagrees with these assertions. First, the Appellant is not alleging that H+ ions are not on the nanometer scale. The Appellant is asserting, however, that H+ ions and "ions" in general do not constitute nanoconductors/nanoparticles as taught by Appellant's invention. In order to understand why such "ions" are not nanoconductors/nanoparticles as taught by Appellant's invention, the Appellant believes that it would be helpful to the Examiner to understand what actually constitutes "nanotechnology". A general discussion of "nanotechnology" is provided in Appellant's "background" section as follows:

"The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. However, it is becoming increasingly difficult to increase the number of elements on a chip using present technologies. At the present rate, in the next few years the theoretical limit of silicon based chips will be reached. Because the number of elements, which can be manufactured on a chip, determines the data storage and processing capabilities of microchips, new technologies are required which will allow for the development of higher performance chips.

Present chip technology is also limited in cases where wires must be crossed on a chip. For the most part, the design of a computer chip is limited to two dimensions. Each time a circuit is forced to cross another circuit, another layer must be added to the chip. This increases the cost and decreases the speed of the resulting chip. A number of alternatives to standard silicon based complementary metal oxide semiconductor ("CMOS") devices have been proposed. The common goal is to produce logic devices on a nanometer scale. Such dimensions are more commonly associated with molecules than integrated circuits.

Integrated circuits and electrical components thereof, which can be produced at a molecular and nanometer scale, include devices such as carbon nanotubes and nanowires, which essentially are nanoscale conductors ("nanoconductors"). Nanoconductors are tiny conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Their structure and fabrication have been widely reported and are well known in the art. Carbon nanotubes, for example, exhibit a unique atomic arrangement, and possess useful physical properties such as one-dimensional electrical behavior, quantum conductance, and ballistic electron transport.

Carbon nanotubes are among the smallest dimensioned nanotube materials with a generally high aspect ratio and small diameter. High-quality single-walled carbon nanotubes

can be grown as randomly oriented, needle-like or spaghetti-like tangled tubules. They can be grown by a number of fabrication methods, including chemical vapor deposition (CVD), laser ablation or electric arc growth. Carbon nanotubes can be grown on a substrate by catalytic decomposition of hydrocarbon containing precursors such as ethylene, methane, or benzene. Nucleation layers, such as thin coatings of Ni, Co, or Fe are often intentionally added onto the substrate surface in order to nucleate a multiplicity of isolated nanotubes. Carbon nanotubes can also be nucleated and grown on a substrate without a metal nucleating layer by using a precursor including one or more of these metal atoms. Semiconductor nanowires can be grown on substrates by similar processes."

The aforementioned language generally describes what is meant by "nanotechnology". Of course, it is understood by those in nanotechnology arts that variations to the aforementioned description and examples re: nanotechnology are likely to arise, but this description can be utilized as a general guideline for the context of "nanotechnology" in which Appellant's invention is provided.

With this in mind, Appellant has provided various examples of <u>nanoconductors</u> in Appellant's specification. For example, the Appellant has referred to <u>nanotubes</u>, <u>nanowires</u>, <u>nanoparticle</u> and even <u>DNA</u>. For example, Appellant's specification at paragraph [0087] indicates that "...Examples of nanoconductors include devices such as, for example, nanowires, nanotubes, and nanoparticles". Appellant's paragraph [0087] also indicates that "The network of nanoconnections depicted in FIG. 3 can be implemented as a network of molecules, including, for example, nanoconductors." Appellant's specification at paragraph [0088] also indicates the following:

"Nanoconnections 304, which are analogous to biological synapses, can be composed of electrical conducting material (i.e., nanoconductors). Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules."

Thus, Appellant's use of nanotechnology-based devices and components relates to multi-atom structures that are built (man-made or natural) or synthesized. DNA, for example, is a naturally constructed multi-atom structure. Free floating ions are not such structures. Atoms and atomic ions do not represent nanoparticles/nanoconductors because "nanotechnology" seeks to use atoms as the <u>building blocks</u> of multi-atom structures. In this light, the H+ ion of Thakoor is not a nanoconductor as taught by Appellant's invention, but rather simply just that --

an ion. Thus, it is not proper to identify the ions of Thakoor as anticipating the nanoconductors of Appellant's invention because one skilled in the art would not recognize an ion as constituting such a nanoconductor (i.e., built or synthesized multi-atom structures such as DNA, nanotubes, nanowires, etc). The ions of Thakoor do not inherently anticipate the nanoconductors taught by Appellant's invention because the Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of nanoconductors (as taught by Appellant's invention) necessarily flows from the teachings of the applied prior art, i.e., Thakoor and the H+ ions.

Regarding the Examiner's assertion that "thin film of hygroscopic chromium trioxide" is used as a dielectric medium, the Appellant believes that it would be helpful to review what constitutes a "dielectric". A dielectric is a material that tends to concentrate an applied electric field within itself. As the dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material.

The chromium trioxide ($Cr_2O_3$) of Thakoor is hygroscopic as Thakoor clearly states. A "hygroscopic" is something that attracts water. $Cr_2O_3$ is also a solid. A dielectric does not "attract" water. In fact, if chromium trioxide were mixed with water, it would form a strong acid that would corrode the nanoconductors, not to mention the chip itself. Chromium trioxide ($Cr_2O_3$) does not tend to concentrate an applied electric field within itself and does not interact with the applied electric field so that charges are redistributed within atoms or molecules of the dielectric. Additionally, chromium trioxide is an electrically conductive oxide. Something that is electrically conductive, by definition, is not used as a dielectric.

Appellant's claims are directed toward nanoconductors that are free to move about in the dielectric medium. Since Appellant's invention is dealing with nanoconductors, i.e., multi-atom structures, it is not at all clear how such multi-atom structures would be free to move about within a solid such as hygroscopic chromium trioxide ($Cr_2O_3$). This is essentially what the Examiner is arguing and does not seem possible, since the definition of a solid is a substance whereby the

constituted parts of the solid are <u>not</u> free to move. This is a significant difference between Appellant's invention and Thakoor.

Additionally, it is important to note that use of H+ ions and the thin film of hygroscopic chromium trioxide in order to achieve the memistor of Thakoor is electrolytic in nature. Thakoor clearly states that the thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serves as a hydrogen ion source (see Page 3132, paragraph under heading "Experimental Details" of Thakoor). The Thakoor device is thus based on an electrolytic configuration, which is the use of an electrolyte and not a dielectric. Thakoor, for example, at page 3133, second column, third paragraph, specifically refers to the use of an electrolyte. The memistor of Thakoor is based on the use of the electrochemical process of electrolysis, which is the production of chemical changes by the passage of current through an <u>electrolyte</u> (not a dielectric). It is also significant to note that the Appellant's invention does not at all rely upon chemical properties but is entirely electro-mechanical. That is, Thakoor is an electrochemical device and based on an electrochemical process.

An example of such an electrochemical process is described in the "Introduction" section of Thakoor, Page 3132, Column 1, lines 34 to Column 2, line 2, where Thakoor states that "...in this paper, we report on the operational characteristics and application potential of a solid-state 'memistor," an analog memory device based on the electrochemical ion transport to/from tungsten oxide in a thin-films structure. The three-terminal devices utilizes a reversible transfer of metal (hydrogen) ions in tungsten oxide..." The use of <u>electrolytes</u> is taught, for example on page 3133, column 1, lines 24-26 of Thakoor where Thakoor refers to "$WO_3$/<u>electrolyte</u> display". The memistor of Thakoor thus is based on the production of chemical changes by the passage of current through an <u>electrolyte</u>.

An electrolyte is a substance containing free <u>ions</u> which behaves as an electrically conductive medium. Electrolytes are generally composed of ions in a solution of some sort. The use of free ions for a substance that behaves as electrically conductive medium, differs from that of a <u>dielectric</u>, which tends to concentrate an applied electric field (e-field) within itself. This is a fundamental and key difference between Thakoor and Appellant's invention. Unlike an electrolyte, such as that employed by Thakoor, as a <u>dielectric</u> interacts with the applied electric

field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. This is not true of electrolytic materials such as that used to create the memistor of Thakoor. This also not true of the hygroscopic chromium trioxide ($Cr_2O_3$) material of Thakoor.

Thus, to summarize, Thakoor's device is based on the use of electrolytes and in particular, the use of chromium trioxide ($Cr_2O_3$) as a hydrogen ion source, whereas Appellant's device is based on the use of a dielectric medium in which nanoconductors (e.g., nanotubes, nanowires, DNA, etc.) are disposed and free to move about. Additionally, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor is not used as a dielectric by Thakoor, and instead also tends to attract water, which could actually damage the nanoparticles and/or chip surface because when chromium trioxide is mixed with water it forms a strong acid. Note that by adding more water to chromium trioxide, more hydrogen ions will be produced, which will make for a very strong acid and thus corrode Appellant's nanoconductors (e.g., nanotubes, nanowires, DNA, etc).

Based on the foregoing, and the requirements of establishing inherency as a basis for an anticipation rejection, the use of hygroscopic chromium trioxide ($Cr_2O_3$) as a hydrogen source in Thakoor can not inherently anticipate the use of a dielectric medium of Appellant's invention, because in relying upon the theory of inherency, the Examiner has not provided a basis in fact and/or technical reasoning to reasonably supporting the determination that the allegedly inherent characteristic of the use of a dielectric medium and nanoconductors (e.g., nanowires, nanotubes, DNA, etc) free to move about in the dielectric medium necessarily flows from the teachings of the Thakoor reference.

Regarding Appellant's claim for "Hebbian learning" the Examiner argued that Thakoor on page 3133, left column, lines 1-14, "teaches the growing or lessening the conductivity of the resistance put a field to adjust the memory". The Examiner argued that such teaching, to one of ordinary skill in the art, can clearly be a learning mechanism. The Appellant asks, how does feature of Thakoor constitute a "learning mechanism"? Where does the learning take place at Thakoor on page 3133, left column, lines 1-14? How is "learning accomplished by "the growing or

lessening the conductivity of the resistance put a field to adjust the memory" of Thakoor. Simply adjusting memory is not "learning". Learning is much more sophisticated and complicated process, which is not achieved simply "adjusting memory". Additionally, and even more importantly, how does such a feature of Thakoor inherently anticipate Hebbian learning?

To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of a learning mechanism. Appellant's Hebbian learning mechanism must operate in a very specific manner in order to provide for Hebbian learning. In order to understand what Hebbian learning is, the Appellant believes it would be helpful to provide a brief overview of Hebbian learning.

Hebbian learning is based on Hebbian theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Introduced by Donald Hebb in 1949, it is also called Hebb's rule and is referred to as Hebbian learning as well. Also known as cell assembly theory, the theory is often summarized as *cells that fire together, wire together*, although this is an oversimplification of the nervous system not to be taken literally.

From the point of view of artificial neurons and artificial neural networks, Hebb's principle can be described as a method of determining how to alter the weights between model neurons as a function of their correlations of their activity in time. The weight between two neurons will increase if the two neurons activate simultaneously (they are correlated); it is reduced if they activate separately. Nodes which tend to be either both positive or both negative at the same time will have strong positive weights while those which tend to be opposite will have strong negative weights. It is sometimes stated more simply as "neurons that fire together, wire together."

This original principle is perhaps the simplest form of weight selection. While this means it can be relatively easily coded into a computer program and used to update the weights for a network, it also prohibits the number of applications of Hebbian learning, at least with respect to software simulations of neural networks.

This is because large neural networks contain massive numbers of synapses and the modification of the synapse in the traditional computing paradigm requires accessing memory. This memory access requires extraordinarily more energy than a physical neural network where synaptic states do not have to be "accessed". Today, the term *Hebbian learning* generally refers to some form of mathematical abstraction of the original principle proposed by Hebb. In this sense, Hebbian learning involves weights between learning nodes being adjusted so that each weight better represents the relationship between the nodes. As such, many learning methods can be considered to be somewhat Hebbian in nature.

The following is a formulaic description of Hebbian learning: (note that many other descriptions are possible)

$$w_{ij} = x_i x_j$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$ and $x_i$ the input for neuron $i$. Note that this is pattern learning (weights updated after every training example). In a Hopfield network, connections $w_{ij}$ are set to zero if $i = j$ (no reflexive connections allowed). With binary neurons (activations either 0 or 1), connections would be set to 1 if the connected neurons have the same activation for a pattern.

Another formulaic description is:

$$w_{ij} = \frac{1}{n} \sum_{k=1}^{p} x_i^k x_j^k ,$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$, $n$ is the dimension of the input vector, $p$ the number of training patterns, and $x_i^k$ the $k$th input for neuron $i$. The Appellant invites the Examiner to view the following web site, which contains a good general overview of Hebbian learning:

http://en.wikipedia.org/wiki/Hebbian_learning

Based on a review of Thakoor and a basic understanding of Hebbian learning it is very clear that Thakoor does not provide for any teaching, suggestion or disclosure of Hebbian learning. Additionally, it is very clear that Thakoor does not inherently anticipate Hebbian learning, and thus the Hebbian learning mechanism provided by Appellant's invention. The Examiner has not provided a basis in fact

and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning necessarily flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory".

Regarding the Examiner's assertion that the Appellant admitted Thakoor teaches "synapse" and a "memistor device", the Appellant respectfully disagrees with this assessment. The Appellant does not admit that the memistor device is a synapse or physical neural network. The memistor device of Thakoor (see FIG. 3 of Thakoor, for example) functions in the context of an autonulling circuit, and is not in and of itself a synapse or a neuron. A review of FIG. 3 of Thakoor, for example, shows that the $WO_3$ based memistor is connected to an offset amplifier and a neuron but in and of itself is not a synapse or a neuron. In FIG. 3 of Thakoor, the neuron to be autonulled is actually separate from the memistor. In no way does Thakoor teach, disclose or suggest actual synapses. Again, FIG. 3 is simply performing an automatic offset nulling of a differential operational amplifier. The terminal labeled Vin depicted in FIG. 3 of Thakoor is where the supposed inputs from synaptic connections would occur but of course these are not shown in Thakoor. In fact, the FIG. 3 circuit is nothing more than a neuron voice of synapses, and certainly, the memistor shown in FIG. 3 is not a synapse and does not even posses pre- and post-synaptic electrodes.

The Examiner's argument that in the broadest reasonable interpretation of this art, a memistor device is interpreted as a physical neural network and pre-synaptic and post-synaptic components are inherent in synapses is incorrect because the memistor as explained above is not a physical neural network nor a synapse. If the Examiner would please identify the pre- and post-synaptic terminals in Thakoor, it would be helpful to the Appellant because the Appellant see three terminals in Thakoor as indicated previously. Instead, the memistor of Thakoor is simply a component, such as a resistor or amplifier, that complements the neuron of Thakoor, but itself is not a physical neural network or a synapse, and is not a pre-synaptic and post-synaptic electrode. Additionally, the Examiner's arguments with respect to inherency fails because the Examiner has not explained how and why the

"missing elements or functions" of the Appellant's claims must necessarily result from the Thakoor reference. That is, the memistor itself is not a physical neural network and does not include a Hebbian learning mechanism, and the use of a dielectric medium comprising a mixture of a dielectric solvent and a plurality of nanoconductors wherein such nanoconductors are free to move about in the dielectric medium. Such features would not "inherently" result from even the slightest modification of Thakoor.

**Argument 3**

The Examiner asserted that regarding Appellant's claim for "Hebbian learning," Thakoor on page 3133, left column, line 1-14, teaches "the growing or lessening the conductivity of the resistance put a field to adjust memory." The Examiner asserted that such teaching, to one of ordinary skill in the art, can clearing be a learning, mechanism, i.e., Hebbian learning.

As far as the Appellant's claim for Hebbian plasticity or anti-Hebbian plasticity is concerned, the Examiner argued that the Thakoor reference anticipates this feature in FIG. 2 of Thakoor. The Examiner argued that FIG. 2 illustrates the variation in resistance with time for several different control voltages. The Examiner argued that plasticity by definition is the ability to develop or adapt in response to the environment. The Examiner further asserted that "another word, the ability to learn or unlearn" and that "as responded above regarding Hebbian learning, the growing or lessening the conductivity of the resistance put a field to adjust memory". The Examiner therefore asserted that the learning or unlearning is being performed by Thakoor.

The Appellant respectfully disagrees with this assessment and notes that the arguments provided above against the Examiner's assertions with respect to Argument 2 and the issue of the Hebbian learning mechanism apply equally against the Examiner's assertions with respect to Argument 3. In the interest of brevity, the Appellant will not repeat these arguments, except to point out again that the Examiner has not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor, and in particular, the

Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory". One of ordinary skill in the art would not see this as teaching or inherently anticipating <u>Hebbian</u> learning. Hebbian learning is a very specific type of neural network learning mechanism, and there is not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor. Simply "growing or lessening the conductivity of the resistance put a field to adjust the memory" does not inherently anticipate the Hebbian learning mechanism of Appellant's invention.

Regarding "Hebbian plasticity" or "anti-Hebbian plasticity," a review of FIG. 2 of Thakoor does not indicate any suggestion, disclosure and/or teaching of Hebbian plasticity or anti-Hebbian plasticity. The Examiner argued that "plasticity" is the ability to develop or adapt in response to the environment, or the ability to learn or unlearn. This is an oversimplification of a concept that is inherently more complex and sophisticated than the definition provided by the Examiner. The memistor is a memory device but not a learning mechanism. The "memistor" characteristics disclosed in FIG. 2 relate only to "turn on" and "turn off" characteristics of the memistor. The memistor exhibits electrochemical analog memory effects but does not learn anything. The memistor merely achieves device programmability over a wide range of resistances.

FIG. 2 of Thakoor is simply a plot of resistance versus time for several control voltages for a turning the device "on" and "off". Thakoor. FIG. 2 does not suggest, disclose or teach any sort of "learning" or "unlearning". The Examiner has merely made a statement that FIG. 2 illustrates an ability to learn or adapting to the environment and hence illustrates "learning". FIG. 2 merely describes "turn-on" and "turn-off" characteristics of the Thakoor device, but does not illustrate a device that has the ability to develop or adapt in response to the environment. The Examiner's arguments do not adequately explain how one skilled in the art would identify FIG. 2 as illustrating plasticity and more importantly, Hebbian plasticity or anti-Hebbian plasticity or the performance of any sort of "learning" or "unlearning". Based on the foregoing, the Appellant submits that there is simply not a basis in

fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian plasticity or anti-Hebbian plasticity flows from the teachings from the test device programming characteristics for variations in resistance of test device with time for several different control voltages of Thakoor's FIG. 2. Plasticity and Hebbian plasticity in particular are very specific types of neural network features, and there is clearly not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian plasticity necessarily flows from the teachings from Thakoor. Thus, FIG. 2 of Thakoor does not inherently anticipate Hebbian and/or anti-Hebbian plasticity, or learning/unlearning and not even plasticity.

**Argument 4**

Regarding Appellant's claim for Hebbian learning, the Examiner again cited Thakoor on page 3133, left column, lines 1-14 where Thakoor teaches the "growing or lessening the conductivity of the resistance put a field to adjust the memory" and asserted that this teaching, to one of ordinary kill in the art, can clearly be a learning mechanism, i.e., Hebbian learning.

The Examiner stated that "as responded earlier, Thakoor teaches 'synapses' and pre-synaptic and post-synaptic components are inherent in synapses".

The Appellant respectfully disagrees with this assessment and notes that the arguments provided above against the Examiner's assertions with respect to Argument 2 and the issue of the Hebbian learning mechanism apply equally against the Examiner's assertions with respect to Argument 4. In the interest of brevity, the Appellant will not repeat these arguments, except to point out again that the Examiner has not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning necessarily flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory". This is simply not a learning mechanism and of course is not Hebbian learning. One of ordinary skill in the art would not see the Examiner's cited teaching of Thakoor or inherently anticipating Hebbian learning. Hebbian learning is a very

specific type of neural network learning mechanism, and there is not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning necessarily flows from the teachings from Thakoor. Simply "growing or lessening the conductivity of the resistance put a field to adjust the memory" does not inherently anticipate the Hebbian learning mechanism of Appellant's invention and one skilled in the art would clearly not see this as a learning mechanism, including Hebbian learning.

**Argument 5**

Regarding Argument 5, the Examiner asserted that as far Appellant's claim for "Hebbian plasticity" or "anti-Hebbian plasticity" is concerned, Thakoor anticipates this feature in FIG. 2. The Examiner asserted that FIG. 2 illustrates the variation in resistance with time for several different control voltages. The Examiner argued that plasticity by definition is the ability to develop or adapt in response to the environment. The Examiner also stated that "another word, the ability to learn or unlearn."

The Examiner also stated that "as responded above regarding Hebbian learning, the growing or lessening the conductivity of resistance put a field to adjust the memory" and argued that the learning or unlearning is being performed.

The Appellant respectfully disagrees with this assessment and notes that the arguments provided above against the Examiner's assertions with respect to Argument 2 and the issue of the Hebbian learning mechanism apply equally against the Examiner's assertions with respect to Argument 5. In the interest of brevity, the Appellant will not repeat these arguments, except to point out again that the Examiner has not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning necessarily flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory". One of ordinary skill in the art would not see this as teaching or inherently anticipating Hebbian learning. Hebbian learning is a very specific type of neural network learning mechanism, and there is not a basis in fact and/or technical

reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor. Simply "growing or lessening the conductivity of the resistance put a field to adjust the memory" does not inherently anticipate the Hebbian learning mechanism of Appellant's invention.

Regarding "Hebbian plasticity" or "anti-Hebbian plasticity," a review of FIG. 2 of Thakoor does not indicate any suggestion, disclosure and/or teaching of Hebbian plasticity or anti-Hebbian plasticity. The Examiner argued that "plasticity" is the ability to develop or adapt in response to the environment, or the ability to learn or unlearn. This is an oversimplification of a concept that is inherently more complex and sophisticated than the definition provided by the Examiner. FIG. 2 of Thakoor is simply a plot of resistance versus time for several control voltages for a turning the device "on" and "off". Thakoor. FIG. 2 does not suggest, disclose or teach any sort of "learning" or "unlearning". The Examiner has merely made a statement that FIG. 2 illustrates an ability to learn or adapting to the environment and hence illustrates "learning".

FIG. 2 merely describes "turn-on" and "turn-off" characteristics of the Thakoor device, but does not illustrate a device that has the ability to develop or adapt in response to the environment. The Examiner's arguments do not adequately explain how one skilled in the art would identify FIG. 2 as illustrating plasticity and more importantly, Hebbian plasticity or anti-Hebbian plasticity or the performance of any sort of "learning" or "unlearning". Based on the foregoing, the Appellant submits that there is simply not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian plasticity or anti-Hebbian plasticity flows from the teachings from the test device programming characteristics for variations in resistance of test device with time for several different control voltages of Thakoor's FIG. 2. Thus, FIG. 2 of Thakoor does not anticipate Hebbian and/or anti-Hebbian plasticity, nor learning/unlearning nor even plasticity.

**Argument 6**

Regarding Argument 6 and Appellant's claim for anti-Hebbian learning, the Examiner argued that Thakoor on page 3133, left column, lines 1-14, teaches the "growing or lessening the conductivity of the resistance put a field to adjust the memory". The Examiner asserted that such teaching, to one of ordinary skill in the art, can clearly be a learning mechanism, i.e., anti-Hebbian learning.

The Appellant asks, how do the features of Thakoor the Examiner cited with respect to page 3133, left column, lines 1-14 constitute a "learning mechanism" and specifically anti-Hebbian learning. How and why are anti-Hebbian learning accomplished by "the growing or lessening the conductivity of the resistance put a field to adjust the memory" of Thakoor. Simply adjusting memory is not "anti-Hebbian learning". Anti-Hebbian learning is a much more sophisticated and complicated process, which is not achieved simply "adjusting memory". Additionally, and even more importantly, how does such a feature of Thakoor inherently anticipate <u>anti-Hebbian</u> learning?

To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "anti-Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of a <u>learning</u> mechanism. Appellant's <u>anti-Hebbian</u> learning mechanism must operate in a very specific manner in order to provide for <u>anti-Hebbian</u> learning. In order to understand what anti-Hebbian learning is, the Appellant believes it would be helpful for the Examiner to refer to the brief overview of Hebbian learning provided early. Hebbian learning is based on <u>Hebbian</u> theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Hebbian theory and Hebbian learning is simply not anticipated inherently or otherwise anywhere within Thakoor. In general, Hebbian learning can thus be implemented in neural networks as a technique for modifying connection based on correlations in pre- and post-synaptic activity. Anti-Hebbian learning is essentially the opposite of Hebbian-based learning techniques. In anti-Hebbian learning, the connections are weakened when connections and/or neurons are correlated in activity, and strengthened when pre- and post-synaptic

activity is anti-correlated. Such anti-Hebbian learning is not suggested, disclosed or taught by Thakoor no page 3133, left column, lines 1-14 cited by the Examiner.

Based on a review of Thakoor and a basic understanding of Hebbian learning it is very clear that Thakoor does not provide for any teaching, suggestion or disclosure of anti-Hebbian learning. Additionally, it is very clear that Thakoor does not inherently anticipate anti-Hebbian learning, and thus the Hebbian learning mechanism provided by Appellant's invention. The Examiner has not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of anti-Hebbian learning necessarily flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory"

The Examiner stated that as responded earlier, that Thakoor teaches "synapse" and pre-synaptic and post-synaptic components are inherent in synapses. The Appellant notes, however, that the memistor of Thakoor is not a synapse but works in association with the neuron to be autonulled (see FIG. 3 of Thakoor).

Regarding the Appellant's claim for nanoconductors is concerned, the Examiner asserted that the Appellant argued that the prior art anticipates this feature with H+ ions, arguing that these are clearly measurable and verifiable to be on the nanometer scale. The Examiner asserted that the Appellant has not brought evidence to prove that H+ ions are not on the nanometer scale as the Examiner asserts.

The Appellant respectfully disagrees with these assertions. First, the Appellant is not alleging that H+ ions are not on the nanometer scale. The Appellant is asserting, however, that H+ ions and "ions" in general do not constitute nanoconductors/nanoparticles taught by Appellant's invention. In order to understand why such "ions" are not nanoconductors/nanoparticles as taught by Appellant's invention, the Appellant believes that it would be helpful to the Examiner to understand what actually constitutes "nanotechnology". A general discussion of "nanotechnology" is provided in Appellant's "background" section as follows:

"The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. However, it is becoming increasingly difficult to increase the number of elements on a chip using present technologies. At the present rate, in the next few years the theoretical limit of silicon based chips will be reached. Because the number of elements, which can be manufactured on a chip, determines the data storage and processing capabilities of microchips, new technologies are required which will allow for the development of higher performance chips.

Present chip technology is also limited in cases where wires must be crossed on a chip. For the most part, the design of a computer chip is limited to two dimensions. Each time a circuit is forced to cross another circuit, another layer must be added to the chip. This increases the cost and decreases the speed of the resulting chip. A number of alternatives to standard silicon based complementary metal oxide semiconductor ("CMOS") devices have been proposed. The common goal is to produce logic devices on a nanometer scale. Such dimensions are more commonly associated with molecules than integrated circuits.

Integrated circuits and electrical components thereof, which can be produced at a molecular and nanometer scale, include devices such as carbon nanotubes and nanowires, which essentially are nanoscale conductors ("nanoconductors"). Nanoconductors are tiny conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Their structure and fabrication have been widely reported and are well known in the art. Carbon nanotubes, for example, exhibit a unique atomic arrangement, and possess useful physical properties such as one-dimensional electrical behavior, quantum conductance, and ballistic electron transport.

Carbon nanotubes are among the smallest dimensioned nanotube materials with a generally high aspect ratio and small diameter. High-quality single-walled carbon nanotubes can be grown as randomly oriented, needle-like or spaghetti-like tangled tubules. They can be grown by a number of fabrication methods, including chemical vapor deposition (CVD), laser ablation or electric arc growth. Carbon nanotubes can be grown on a substrate by catalytic decomposition of hydrocarbon containing precursors such as ethylene, methane, or benzene. Nucleation layers, such as thin coatings of Ni, Co, or Fe are often intentionally added onto the substrate surface in order to nucleate a multiplicity of isolated nanotubes. Carbon nanotubes can also be nucleated and grown on a substrate without a metal nucleating layer by using a precursor including one or more of these metal atoms. Semiconductor nanowires can be grown on substrates by similar processes."

The aforementioned language generally describes what is meant by "nanotechnology". Of course, it is understood by those in nanotechnology arts that variations to the aforementioned description and examples re: nanotechnology are likely to arise, but this description can be utilized as a general guideline for the context of "nanotechnology" in which Appellant's invention is provided.

With this in mind, Appellant has provided various examples of nanoconductors in Appellant's specification. For example, the Appellant has referred to nanotubes, nanowires, nanoparticle and even DNA. For example, Appellant's specification at paragraph [0087] indicates that "...Examples of nanoconductors include devices such as, for example, nanowires, nanotubes, and nanoparticles". Appellant's paragraph [0087] also indicates that "The network of nanoconnections depicted in FIG. 3 can be implemented as a network of molecules, including, for example, nanoconductors." Appellant's specification at paragraph [0088) also indicates the following:

> "Nanoconnections 304, which are analogous to biological synapses, can be composed of electrical conducting material (i.e., nanoconductors). Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules."

Thus, Appellant's use of nanotechnology-based devices and components relates to multi-atom structures that are built (man-made or natural) or synthesized. DNA, for example, is a naturally constructed multi-atom structure. Free floating ions are not such structures. Atoms and atomic ions do not represent nanoparticles/nanoconductors because "nanotechnology" seeks to use atoms as the building blocks of multi-atom structures. In this light, the H+ ion of Thakoor is not a nanoconductor as taught by Appellant's invention, but rather simply just that -- an ion. Thus, it is not proper to identify the ions of Thakoor as anticipating the nanoconductors of Appellant's invention because one skilled in the art would not recognize an ion as constituting such a nanoconductor (i.e., built or synthesized multi-atom structures such as DNA, nanotubes, nanowires, etc). The ions of Thakoor do not inherently anticipate the nanoconductors taught by Appellant's invention because the Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of nanoconductors (as taught by Appellant's invention) necessarily flows from the teachings of the applied prior art, i.e., Thakoor and the H+ ions.

**Argument 7**

Regarding Argument 7, the Examiner argued that the Appellant freely admitted that $H_xWO_3$ is a chemical compound. The Examiner stated that nanowires or nanoparticles by definition, are components of nanotechnology to create electrical circuits out of chemical compounds that are capable of being formed into extremely small circuits. The Appellant respectfully disagrees with this assessment. $H_xWO_3$ is simply a chemical compound and is not a nanowire, a nanotube, DNA, or any other type of nanoconductor as taught by Appellant's invention. Simply because a thing is a chemical compound does not mean that it functions as a nanoconductor under the definition of nanotechnology.

The $H_xWO_3$ material of Thakoor does not inherently anticipate the nanoconductors taught by Appellant's invention because the Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of nanoconductors (as taught by Appellant's invention) <u>necessarily</u> flows from the teachings of Thakoor.

**Argument 8**

Regarding Argument 8, the Examiner reminded the Appellant that although the claims are interpreted in light of the specification, limitations from the specification are not read into the claims. The Examiner argued that in this argument, the Appellant admitted that Thakoor teaches "synapses" and a "memistor device". The Examiner argued that in the broadest reasonable interpretation of this art, a memistor device is interpreted as a physical neural network and pre-synaptic and post-synaptic components are inherent in synapses.

The Appellant respectfully disagrees with this assessment. In the broadest reasonable interpretation of Thakoor, the memistor device is neither a synapse nor a physical neural network, but simply a device that complements the neuron to be annulled (see FIG. 3 of Thakoor). Thus the memistor device itself does not teach, suggest or anticipate a physical neural network or two separate pre-synaptic and post-synaptic components.

The Examiner further argued that as far as Appellant's claim for "nanoconductors" is concerned, the prior art anticipates this feature with H+ ions,

which the Examiner argued are clearly measurable and verifiable to be on the nanometer scale. The Examiner asserted that the Appellant has not brought evidence to provide that H+ ions are not on the nanometer scale as the Examiner asserts.

The Examiner argued that the "nanoconductors" in Thakoor are "H+ ions" (or "H+ ions" as the prior art calls them). The Examiner argued that they are suspended in a "thin film of hygroscopic chromium trioxide" as the prior art calls them. The Examiner asserted that this is the "dielectric medium" of Appellant's invention.

The Appellant respectfully disagrees with these assertions. First, the Appellant is not alleging that H+ ions are not on the nanometer scale. The Appellant is asserting, however, that H+ ions and "ions" in general do not constitute nanoconductors/nanoparticles taught by Appellant's invention. In order to understand why such "ions" are not nanoconductors/nanoparticles as taught by Appellant's invention, the Appellant believes that it would be helpful to the Examiner to understand what actually constitutes "nanotechnology". A general discussion of "nanotechnology" is provided in Appellant's "background" section as follows:

"The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. However, it is becoming increasingly difficult to increase the number of elements on a chip using present technologies. At the present rate, in the next few years the theoretical limit of silicon based chips will be reached. Because the number of elements, which can be manufactured on a chip, determines the data storage and processing capabilities of microchips, new technologies are required which will allow for the development of higher performance chips.

Present chip technology is also limited in cases where wires must be crossed on a chip. For the most part, the design of a computer chip is limited to two dimensions. Each time a circuit is forced to cross another circuit, another layer must be added to the chip. This increases the cost and decreases the speed of the resulting chip. A number of alternatives to standard silicon based complementary metal oxide semiconductor ("CMOS") devices have been proposed. The common goal is to produce logic devices on a nanometer

scale. Such dimensions are more commonly associated with molecules than integrated circuits.

Integrated circuits and electrical components thereof, which can be produced at a molecular and nanometer scale, include devices such as carbon nanotubes and nanowires, which essentially are nanoscale conductors ("nanoconductors"). Nanoconductors are tiny conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Their structure and fabrication have been widely reported and are well known in the art. Carbon nanotubes, for example, exhibit a unique atomic arrangement, and possess useful physical properties such as one-dimensional electrical behavior, quantum conductance, and ballistic electron transport.

Carbon nanotubes are among the smallest dimensioned nanotube materials with a generally high aspect ratio and small diameter. High-quality single-walled carbon nanotubes can be grown as randomly oriented, needle-like or spaghetti-like tangled tubules. They can be grown by a number of fabrication methods, including chemical vapor deposition (CVD), laser ablation or electric arc growth. Carbon nanotubes can be grown on a substrate by catalytic decomposition of hydrocarbon containing precursors such as ethylene, methane, or benzene. Nucleation layers, such as thin coatings of Ni, Co, or Fe are often intentionally added onto the substrate surface in order to nucleate a multiplicity of isolated nanotubes. Carbon nanotubes can also be nucleated and grown on a substrate without a metal nucleating layer by using a precursor including one or more of these metal atoms. Semiconductor nanowires can be grown on substrates by similar processes."

The aforementioned language generally describes what is meant by "nanotechnology". Of course, it is understood by those in nanotechnology arts that variations to the aforementioned description and examples re: nanotechnology are likely to arise, but this description can be utilized as a general guideline for the context of "nanotechnology" in which Appellant's invention is provided.

With this in mind, Appellant has provided various examples of <u>nanoconductors</u> in Appellant's specification. For example, the Appellant has referred to <u>nanotubes</u>, <u>nanowires</u>, <u>nanoparticle</u> and even <u>DNA</u>. For example, Appellant's specification at paragraph [0087] indicates that "...Examples of nanoconductors include devices such as, for example, nanowires, nanotubes, and nanoparticles". Appellant's paragraph [0087] also indicates that "The network of nanoconnections depicted in FIG. 3 can be implemented as a network of molecules, including, for example, nanoconductors." Appellant's specification at paragraph [0088) also indicates the following:

"Nanoconnections 304, which are analogous to biological synapses, can be composed of electrical conducting material (i.e., nanoconductors). Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules."

Thus, Appellant's use of nanotechnology-based devices and components relates to multi-atom structures that are built (man-made or natural) or synthesized. DNA, for example, is a naturally constructed multi-atom structure. Free floating ions are not such structures. Atoms and atomic ions do not represent nanoparticles/nanoconductors because "nanotechnology" seeks to use atoms as the building blocks of multi-atom structures. In this light, the H+ ion of Thakoor is not a nanoconductor as taught by Appellant's invention, but rather simply just that -- an ion. Thus, it is not proper to identify the ions of Thakoor as anticipating the nanoconductors of Appellant's invention because one skilled in the art would not recognize an ion as constituting such a nanoconductor (i.e., built or synthesized multi-atom structures such as DNA, nanotubes, nanowires, etc). The ions of Thakoor do not inherently anticipate the nanoconductors taught by Appellant's invention because the Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of nanoconductors (as taught by Appellant's invention) necessarily flows from the teachings of the applied prior art, i.e., Thakoor and the H+ ions.

Regarding Appellant's claim for "Hebbian learning" the Examiner argued that Thakoor on page 3133, left column, lines 1-14, "teaches the growing or lessening the conductivity of the resistance put a field to adjust the memory". The Examiner argued that such teaching, to one of ordinary skill in the art, can clearly be a learning mechanism. The Appellant asks, wow does feature of Thakoor constitute a "learning mechanism"? How is "learning accomplished by "the growing or lessening the conductivity of the resistance put a field to adjust the memory" of Thakoor. Simply adjusting memory is not "learning". Learning is much more sophisticated and complicated process, which is not achieved simply "adjusting memory". Additionally, and even more importantly, how does such a feature of Thakoor inherently anticipate Hebbian learning?

To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of a learning mechanism. Appellant's Hebbian learning mechanism must operate in a very specific manner in order to provide for Hebbian learning. In order to

understand what Hebbian learning is, the Appellant believes it would be helpful to provide a brief overview of Hebbian learning.

Hebbian learning is based on Hebbian theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Introduced by Donald Hebb in 1949, it is also called Hebb's rule and is referred to as Hebbian learning as well. Also known as cell assembly theory, the theory is often summarized as *cells that fire together, wire together*, although this is an oversimplification of the nervous system not to be taken literally.

From the point of view of artificial neurons and artificial neural networks, Hebb's principle can be described as a method of determining how to alter the weights between model neurons as a function of their correlations of their activity in time. The weight between two neurons will increase if the two neurons activate simultaneously (they are correlated); it is reduced if they activate separately. Nodes which tend to be either both positive or both negative at the same time will have strong positive weights while those which tend to be opposite will have strong negative weights. It is sometimes stated more simply as "neurons that fire together, wire together."

This original principle is perhaps the simplest form of weight selection. While this means it can be relatively easily coded into a computer program and used to update the weights for a network, it also prohibits the number of applications of Hebbian learning, at least with respect to software simulations of neural networks. This is because large neural networks contain massive numbers of synapses and the modification of the synapse in the traditional computing paradigm requires accessing memory. This memory access requires extraordinarily more energy than a physical neural network where synaptic states do not have to be "accessed". Today, the term *Hebbian learning* generally refers to some form of mathematical abstraction of the original principle proposed by Hebb. In this sense, Hebbian learning involves weights between learning nodes being adjusted so that each weight better represents the relationship between the nodes. As such, many learning methods can be considered to be somewhat Hebbian in nature.

The following is a formulaic description of Hebbian learning: (note that many other descriptions are possible)

$$w_{ij} = x_i x_j$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$ and $x_i$ the input for neuron $i$. Note that this is pattern learning (weights updated after every training example). In a Hopfield network, connections $w_{ij}$ are set to zero if $i = j$ (no reflexive connections allowed). With binary neurons (activations either 0 or 1), connections would be set to 1 if the connected neurons have the same activation for a pattern.

Another formulaic description is:

$$w_{ij} = \frac{1}{n} \sum_{k=1}^{p} x_i^k x_j^k ,$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$, $n$ is the dimension of the input vector, $p$ the number of training patterns, and $x_i^k$ the $k$th input for neuron $i$. The Appellant invites the Examiner to view the following web site, which contains a good general overview of Hebbian learning:

http://en.wikipedia.org/wiki/Hebbian_learning

Based on a review of Thakoor and a basic understanding of Hebbian learning it is very clear that Thakoor does not provide for any teaching, suggestion or disclosure of Hebbian learning. Additionally, it is very clear that Thakoor does not inherently anticipate Hebbian learning, and thus the Hebbian learning mechanism provided by Appellant's invention. The Examiner has not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory"

Regarding "Hebbian plasticity" or "anti-Hebbian plasticity," a review of FIG. 2 of Thakoor does not indicate any suggestion, disclosure and/or teaching of Hebbian plasticity or anti-Hebbian plasticity. The Examiner argued that "plasticity" is the ability to develop or adapt in response to the environment, or the ability to learn or

unlearn. This is an oversimplification of a concept that is inherently more complex and sophisticated than the definition provided by the Examiner. FIG. 2 of Thakoor is simply a plot of resistance versus time for several control voltages for a turning the device "on" and "off". Thakoor. FIG. 2 does not suggest, disclose or teach any sort of "learning" or "unlearning". The Examiner has merely made a statement that FIG. 2 illustrates an ability to learn or adapting to the environment and hence illustrates "learning". FIG. 2 merely describes "turn-on" and "turn-off" characteristics of the Thakoor device, but does not illustrate a device that has the ability to develop or adapt in response to the environment. The Examiner's arguments do not adequately explain how one skilled in the art would identify FIG. 2 as illustrating plasticity and more importantly, Hebbian plasticity or anti-Hebbian plasticity or the performance of any sort of "learning" or "unlearning". Based on the foregoing, the Appellant submits that there is simply not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian plasticity or anti-Hebbian plasticity flows from the teachings from the test device programming characteristics for variations in resistance of test device with time for several different control voltages of Thakoor's FIG. 2. Thus, FIG. 2 of Thakoor does not anticipate Hebbian and/or anti-Hebbian plasticity, nor learning/unlearning nor even plasticity.

**Argument 9**

Regarding Argument 9, the Examiner asserted that the Appellant freely admitted that $H_xWO_3$ is a chemical compound. The Examiner stated that nanowires or nanoparticles by definition, are components of nanotechnology to create electrical circuits out of chemical compounds that are capable of being formed into extremely small circuits. The Appellant respectfully disagrees with this assessment. $H_xWO_3$ is simply a chemical compound and is not a nanowire, a nanotube, DNA, or any other type of nanoconductor as taught by Appellant's invention. Simply because a thing is a chemical compound does not mean that it functions as a nanoconductor under the definition of nanotechnology.

A nanowire by definition is a much more complicated and versatile device than just a chemical compound such as $H_xWO_3$. In order to understand what a nanowire

is, the Appellant believes it would be helpful for the Examiner to review the information about nanowires freely available at the following web site:

http://en.wikipedia.org/wiki/Nanowire

The first thing to appreciate about a nanowire is that it is a wire. The $H_xWO_3$ of Thakoor is not a wire. A nanowire is a <u>wire</u> of dimensions of the order of a nanometer ($10^{-9}$ meters). Alternatively, nanowires can be defined as structures that have a lateral size constrained to tens of nanometers or less and an unconstrained longitudinal size. At these scales, quantum mechanical effects are important — hence such wires are also known as "quantum wires". Many different types of nanowires exist, including metallic (e.g., Ni, Pt, Au), semiconducting (e.g., InP, Si, GaN, etc.), and insulating (e.g., $SiO_2$,$TiO_2$). Molecular nanowires are composed of repeating molecular units either organic (e.g. DNA) or inorganic (e.g. $Mo_6S_{9-x}I_x$).

Typical nanowires exhibit aspect ratios (the ratio between length to width) of 1000 or more. As such they are often referred to as 1-Dimensional materials. Nanowires have many interesting properties that are not seen in bulk or 3-D materials. This is because electrons in nanowires are quantum confined laterally and thus occupy energy levels that are different from the traditional continuum of energy levels or bands found in bulk materials. Peculiar features of this quantum confinement exhibited by certain nanowires such as carbon nanotubes manifest themselves in discrete values of the electrical conductance. Such discrete values arise from a quantum mechanical restraint on the number of electrons that can travel through the wire at the nanometer scale. These discrete values are often referred to as the quantum of conductance. Examples of nanowires include inorganic molecular nanowires ($Mo_6S_{9-x}I_x$), which have a diameter of 0.9 nm, and can be hundreds of micrometers long. Other important examples are based on semiconductors such as InP, Si, GaN, etc., dielectrics (e.g. $SiO_2$,$TiO_2$), or metals (e.g. Ni, Pt).

The $H_xWO_3$ material of Thakoor is therefore not a nanowire. FIG. 1 of Thakoor and page 3132-3133 of Thakoor make it clear that Thakoor is not a wire but merely a layer of the memistor device. The $H_xWO_3$ compound of Thakoor is the result of a chemical reaction wherein an influx of H+ ions react with the $WO_3$ layer to form the

$H_xWO_3$ compound, whereas the nanowires of Appellant's invention are prepared in a dielectric medium and do not occur as a result of a chemical reaction. Appellant's nanowires are pre-disposed in a dielectric medium rather than as a result of a chemical reaction as part of the process of forming the memistor device. It is also significant to note that $H_xWO_3$ is tungstic acid (see page 3133, left column, line 4 of Thakoor). Mixing tungstic acid with Appellant's dielectric medium does not make sense because the acid would destroy the viability of the dielectric medium.

The $H_xWO_3$ compound (i.e., Tungstic Acid) of Thakoor simply does not inherently or directly anticipate the nanowires of Appellant's invention. The Examiner has simply not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of a nanowire flows from the teachings from the $H_xWO_3$ compound of Thakoor. Thus, the $H_xWO_3$ compound (i.e., Tungstic Acid) of Thakoor does not anticipate the nanowires of Appellant's invention.

**Argument 10**

Regarding Argument 10, the Examiner asserted that the "nanoconductors" in Thakoor are "H+ ions". The Examiner asserted that they are suspended in a "thin film of hygroscopic chromium trioxide" and asserted that this is a dielectric medium. Regarding the Examiner's assertion that "thin film of hygroscopic chromium trioxide" is a dielectric medium, the Appellant believes that it would be helpful to review what constitutes a "dielectric". A dielectric is a material that tends to concentrate an applied electric field (e-field) within itself. As the dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. The chromium trioxide ($Cr_2O_3$) of Thakoor is hygroscopic as Thakoor clearly states. A "hygroscopic" is something that attracts water. $Cr_2O_3$ is also a solid. A dielectric does not "attract" water. In fact, if a dielectric did attract water the water itself would damage Appellant's dielectric medium and plurality of nanoconductors disposed in the dielectric medium, so it would not make sense to use a "hygroscopic" material such as that of Thakoor. Chromium trioxide ($Cr_2O_3$) does

not tend to concentrate an applied electric field within itself and does not interact with the applied electric field so that charges are redistributed within atoms or molecules of the dielectric.

Additionally, it is important to note that use of H+ ions and the thin film of hygroscopic chromium trioxide in order to achieve the memistor of Thakoor is electrolytic in nature. Thakoor clearly states that the thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serves as a hydrogen ion source (see Page 3132, paragraph under heading "Experimental Details" of Thakoor). The Thakoor device is thus based on an electrolytic configuration, that is, the use of an electrolyte and not a dielectric. Thakoor, for examples, at page 3133, second column, third paragraph, specifically refers to the use of an electrolyte. The memistor of Thakoor is based on the use of the electrochemical process of electrolysis, which is the production of chemical changes by the passage of current through an electrolyte (not a dielectric).

An example of such an electrochemical process is described in the "Introduction" section of Thakoor, Page 3132, Column 1, lines 34 to Column 2, line 2, where Thakoor states that "...in this paper, we report on the operational characteristics and application potential of a solid-state 'memistor," an analog memory device based on the electrochemical ion transport to/from tungsten oxide in a thin-films structure. The three-terminal devices utilizes a reversible transfer of metal (hydrogen) ions in tungsten oxide..." The use of electrolytes is taught, for example on page 3133, column 1, lines 24-26 of Thakoor where Thakoor refers to "$WO_3$/electrolyte display". The memistor of Thakoor is based on the production of chemical changes by the passage of current through an electrolyte.

An electrolyte is a substance containing free ions which behaves as an electrically conductive medium. Electrolytes are generally composed of ions in a solution of some sort. The use of free ions for a substance that behaves as electrically conductive medium, differs from that of a dielectric, which tends to concentrate an applied electric field (e-field) within itself. This is a fundamental and key difference between Thakoor and Appellant's invention. Unlike an electrolyte, such as that employed by Thakoor, as a dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This

redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. This is not true of electrolytic materials such as that used to create the memistor of Thakoor. This also not true of the hygroscopic chromium trioxide ($Cr_2O_3$) material of Thakoor.

Thus, to summarize, Thakoor's device is based on the use of electrolytes, whereas Appellant's device utilizes a dielectric. Additionally, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor is not a dielectric and instead tends to attract water, which would actually damage the dielectric configuration of Appellant's invention. Based on the foregoing, and requirements of establishing inherency as a basis for anticipation, one skilled in the art would not come to the conclusion that the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor inherently anticipates the dielectric medium of Appellant's invention, because in relying upon the theory of inherency, the Examiner has not provided a basis in fact and/or technical reasoning to reasonably supporting the determination that the allegedly inherent characteristic of the use of a dielectric medium in which nanoconductors (e.g., nanotubes, nanowires, DNA, etc) are free to move about necessarily flows from the teachings of the Thakoor reference. The evidence provided above proves the opposite.

**Argument 11**

Regarding Argument 11, the Examiner asserted that as far as Appellant's claim for "nanotechnology" is concerned, the prior art anticipates this feature with H+ ions and argued that these ions are clearly measurable and verifiable to be on the nanometer scale. The Examiner asserted that the Appellant has not brought evidence to prove that the H+ ions are not on the nanometer scale, as Examiner asserts.

The Examiner argued that the "nanoconductors" in Thakoor are "H+ ions" as Appellant calls them (or "H+ ions" as the prior art calls them). The Examiner asserted that they are suspended in a "thin film of hygroscopic chromium trioxide" as the prior art calls it. The Examiner asserted that this is the same dielectric medium as Appellant's invention.

The Appellant respectfully disagrees with these assertions. First, the Appellant is not alleging that H+ ions are not on the nanometer scale. The Appellant is

asserting, however, that H+ ions and "ions" in general do not constitute nanoconductors/nanoparticles taught by Appellant's invention. In order to understand why such "ions" are not nanoconductors/nanoparticles as taught by Appellant's invention, the Appellant believes that it would be helpful to the Examiner to understand what actually constitutes "nanotechnology". A general discussion of "nanotechnology" is provided in Appellant's "background" section as follows:

"The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. However, it is becoming increasingly difficult to increase the number of elements on a chip using present technologies. At the present rate, in the next few years the theoretical limit of silicon based chips will be reached. Because the number of elements, which can be manufactured on a chip, determines the data storage and processing capabilities of microchips, new technologies are required which will allow for the development of higher performance chips.

Present chip technology is also limited in cases where wires must be crossed on a chip. For the most part, the design of a computer chip is limited to two dimensions. Each time a circuit is forced to cross another circuit, another layer must be added to the chip. This increases the cost and decreases the speed of the resulting chip. A number of alternatives to standard silicon based complementary metal oxide semiconductor ("CMOS") devices have been proposed. The common goal is to produce logic devices on a nanometer scale. Such dimensions are more commonly associated with molecules than integrated circuits.

Integrated circuits and electrical components thereof, which can be produced at a molecular and nanometer scale, include devices such as carbon nanotubes and nanowires, which essentially are nanoscale conductors ("nanoconductors"). Nanoconductors are tiny conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Their structure and fabrication have been widely reported and are well known in the art. Carbon nanotubes, for example, exhibit a unique atomic arrangement, and possess useful physical properties such as one-dimensional electrical behavior, quantum conductance, and ballistic electron transport.

Carbon nanotubes are among the smallest dimensioned nanotube materials with a generally high aspect ratio and small diameter. High-quality single-walled carbon nanotubes can be grown as randomly oriented, needle-like or spaghetti-like tangled tubules. They can be grown by a number of fabrication methods, including chemical vapor deposition (CVD), laser ablation or electric arc growth. Carbon nanotubes can be grown on a substrate by catalytic decomposition of hydrocarbon containing precursors such as ethylene, methane, or benzene. Nucleation layers, such as thin coatings of Ni, Co, or Fe are often intentionally added onto the substrate surface in order to nucleate a multiplicity of isolated nanotubes.

Carbon nanotubes can also be nucleated and grown on a substrate without a metal nucleating layer by using a precursor including one or more of these metal atoms. Semiconductor nanowires can be grown on substrates by similar processes."

The aforementioned language generally describes what is meant by "nanotechnology". Of course, it is understood by those in nanotechnology arts that variations to the aforementioned description and examples re: nanotechnology are likely to arise, but this description can be utilized as a general guideline for the context of "nanotechnology" in which Appellant's invention is provided.

With this in mind, Appellant has provided various examples of <u>nanoconductors</u> in Appellant's specification. For example, the Appellant has referred to <u>nanotubes</u>, <u>nanowires</u>, <u>nanoparticle</u> and even <u>DNA</u>. For example, Appellant's specification at paragraph [0087] indicates that "...Examples of nanoconductors include devices such as, for example, nanowires, nanotubes, and nanoparticles". Appellant's paragraph [0087] also indicates that "The network of nanoconnections depicted in FIG. 3 can be implemented as a network of molecules, including, for example, nanoconductors." Appellant's specification at paragraph [0088) also indicates the following:

"Nanoconnections 304, which are analogous to biological synapses, can be composed of electrical conducting material (i.e., nanoconductors). Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules."

Thus, Appellant's use of nanotechnology-based devices and components relates to multi-atom structures that are built (man-made or natural) or synthesized. DNA, for example, is a naturally constructed multi-atom structure. Free floating ions are not such structures. Atoms and atomic ions do not represent nanoparticles/nanoconductors because "nanotechnology" seeks to use atoms as the <u>building blocks</u> of multi-atom structures. In this light, the H+ ion of Thakoor is not a nanoconductor as taught by Appellant's invention, but rather simply just that -- an ion. Thus, it is not proper to identify the <u>ions</u> of Thakoor as anticipating the <u>nanoconductors</u> of Appellant's invention because one skilled in the art would <u>not</u> recognize an ion as constituting such a nanoconductor (i.e., built or synthesized

multi-atom structures such as DNA, nanotubes, nanowires, etc). The ions of Thakoor do not inherently anticipate the nanoconductors taught by Appellant's invention because the Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of nanoconductors (as taught by Appellant's invention) necessarily flows from the teachings of the applied prior art, i.e., Thakoor and the H+ ions.

Regarding the Examiner's assertion that "thin film of hygroscopic chromium trioxide" is used by Thakoor as a dielectric medium, the Appellant believes that it would be helpful to review what constitutes a "dielectric". A dielectric is a material that tends to concentrate an applied electric field within itself. As the dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. The chromium trioxide ($Cr_2O_3$) of Thakoor is hygroscopic as Thakoor clearly states. A "hygroscopic" is something that attracts water. $Cr_2O_3$ is also a solid. A dielectric does not "attract" water. In fact, if a dielectric did attract water the water itself would damage Appellant's dielectric medium and plurality of nanoconductors disposed (and free to move about) in the dielectric medium, so it would not make sense to use a "hygroscopic" material such as that of Thakoor. Chromium trioxide ($Cr_2O_3$) does not tend to concentrate an applied electric field within itself and does not interact with the applied electric field so that charges are redistributed within atoms or molecules of the dielectric.

Additionally, it is important to note that use of H+ ions and the thin film of hygroscopic chromium trioxide in order to achieve the memistor of Thakoor is electrolytic in nature. Thakoor clearly states that the thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serves as a hydrogen ion source (see Page 3132, paragraph under heading "Experimental Details" of Thakoor). The Thakoor device is thus based on an electrolytic configuration, that is, the use of an electrolyte and not a dielectric. Thakoor, for examples, at page 3133, second column, third paragraph, specifically refers to the use of an electrolyte. The memistor of Thakoor is based on the use of the electrochemical process of electrolysis, which is the

production of chemical changes by the passage of current through an <u>electrolyte</u> (not a dielectric).

An example of such an electrochemical process is described in the "Introduction" section of Thakoor, Page 3132, Column 1, lines 34 to Column 2, line 2, where Thakoor states that "...in this paper, we report on the operational characteristics and application potential of a solid-state 'memistor," an analog memory device based on the electrochemical ion transport to/from tungsten oxide in a thin-films structure. The three-terminal devices utilizes a reversible transfer of metal (hydrogen) ions in tungsten oxide..." The use of <u>electrolytes</u> is taught, for example on page 3133, column 1, lines 24-26 of Thakoor where Thakoor refers to "$WO_3$/<u>electrolyte</u> display". The memistor of Thakoor is based on the production of chemical changes by the passage of current through an <u>electrolyte</u>.

An electrolyte is a substance containing free <u>ions</u> which behaves as an electrically conductive medium. Electrolytes are generally composed of ions in a solution of some sort. The use of free ions for a substance that behaves as electrically conductive medium, differs from that of the use of a <u>dielectric</u>, which tends to concentrate an applied electric field (e-field) within itself. This is a fundamental and key difference between Thakoor and Appellant's invention. Unlike an electrolyte, such as that employed by Thakoor, as a <u>dielectric</u> interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the <u>dielectric</u> material. This is <u>not</u> true of electrolytic materials such as that used to create the memistor of Thakoor. This also not true of the hygroscopic chromium trioxide ($Cr_2O_3$) material of Thakoor.

Thus, to summarize, Thakoor's device is based on the use of electrolytes, whereas Appellant's device is based on the use of a dielectric. Additionally, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor tends to attract water, which would actually damage the dielectric configuration of Appellant's invention. $Cr_2O_3$ reacts with water, a strong acid is produced, which would corrode Appellant's nanoconductors, so it would not make sense to use $Cr_2O_3$ as a dielectric in which nanoconductors (e.g., nanowires, nanotubes, DNA, etc.) are free to move about. Based on the foregoing, and requirements of establishing inherency as a basis for

anticipation, one skilled in the art would not come to the conclusion that the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor inherently anticipates the use of a dielectric medium of Appellant's invention, because in relying upon the theory of inherency, the Examiner has not provided a basis in fact and/or technical reasoning to reasonably supporting the determination that the allegedly inherent characteristic of the use of a dielectric medium (in which nanoconductors are free to move about) <u>necessarily</u> flows from the teachings of the Thakoor reference. The evidence provided above proves the opposite.

Regarding Appellant's claim for "Hebbian learning" the Examiner argued that Thakoor on page 3133, left column, lines 1-14, "teaches the growing or lessening the conductivity of the resistance put a field to adjust the memory". The Examiner argued that such teaching, to one of ordinary skill in the art, can clearly be a learning mechanism. The Appellant asks, wow does feature of Thakoor constitute a "learning mechanism"? How is "learning accomplished by "the growing or lessening the conductivity of the resistance put a field to adjust the memory" of Thakoor. Simply adjusting memory is not "learning". Learning is much more sophisticated and complicated process, which is not achieved simply "adjusting memory". Additionally, and even more importantly, how does such a feature of Thakoor inherently anticipate <u>Hebbian</u> learning?

To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of a <u>learning</u> mechanism. Appellant's <u>Hebbian</u> learning mechanism must operate in a very specific manner in order to provide for <u>Hebbian</u> learning. In order to understand what Hebbian learning is, the Appellant believes it would be helpful to provide a brief overview of Hebbian learning.

Hebbian learning is based on <u>Hebbian</u> theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Introduced by Donald Hebb in 1949, it is also called Hebb's rule and is referred to as Hebbian learning as well. Also known as cell assembly theory, the theory is

often summarized as *cells that fire together, wire together*, although this is an oversimplification of the nervous system not to be taken literally.

From the point of view of artificial neurons and artificial neural networks, Hebb's principle can be described as a method of determining how to alter the weights between model neurons as a function of their correlations of their activity in time. The weight between two neurons will increase if the two neurons activate simultaneously (they are correlated); it is reduced if they activate separately. Nodes which tend to be either both positive or both negative at the same time will have strong positive weights while those which tend to be opposite will have strong negative weights. It is sometimes stated more simply as "neurons that fire together, wire together."

This original principle is perhaps the simplest form of weight selection. While this means it can be relatively easily coded into a computer program and used to update the weights for a network, it also prohibits the number of applications of Hebbian learning, at least with respect to software simulations of neural networks. This is because large neural networks contain massive numbers of synapses and the modification of the synapse in the traditional computing paradigm requires accessing memory. This memory access requires extraordinarily more energy than a physical neural network where synaptic states do not have to be "accessed". Today, the term *Hebbian learning* generally refers to some form of mathematical abstraction of the original principle proposed by Hebb. In this sense, Hebbian learning involves weights between learning nodes being adjusted so that each weight better represents the relationship between the nodes. As such, many learning methods can be considered to be somewhat Hebbian in nature.

The following is a formulaic description of Hebbian learning: (note that many other descriptions are possible)

$$w_{ij} = x_i x_j$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$ and $x_i$ the input for neuron $i$. Note that this is pattern learning (weights updated after every training example). In a Hopfield network, connections $w_{ij}$ are set to zero if $i = j$ (no reflexive connections allowed). With binary neurons (activations either 0 or 1),

connections would be set to 1 if the connected neurons have the same activation for a pattern.

Another formulaic description is:

$$w_{ij} = \frac{1}{n} \sum_{k=1}^{p} x_i^k x_j^k ,$$

where $w_{ij}$ is the weight of the connection from neuron *j* to neuron *i*, *n* is the dimension of the input vector, *p* the number of training patterns, and $x_i^k$ the *k*th input for neuron *i*. The Appellant invites the Examiner to view the following web site, which contains a good general overview of Hebbian learning:

http://en.wikipedia.org/wiki/Hebbian_learning

Based on a review of Thakoor and a basic understanding of Hebbian learning it is very clear that Thakoor does not provide for any teaching, suggestion or disclosure of Hebbian learning. Additionally, it is very clear that Thakoor does not inherently anticipate Hebbian learning, and thus the Hebbian learning mechanism provided by Appellant's invention. The Examiner has not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory"

**Argument 12**

Regarding Argument 12, the Examiner argued that the "nanoconductors" in Thakoor are "H + ions" and additionally that they are suspended in a thin film of hygroscopic chromium trioxide and argued that this thin film is the same dielectric medium of Appellant's invention. The Examiner asserted that the dielectric solvent is disclosed as a "hygroscopic i.e. moisture film" in Thakoor.

Regarding the Examiner's assertion that "thin film of hygroscopic chromium trioxide" is used as a dielectric medium in which nanoconductors (e.g., nanowires, nanotubes, DNA, etc) are free to move about, the Appellant believes that it would be helpful to review what constitutes a "dielectric". A dielectric is a material that

tends to concentrate an applied electric field within itself. As the dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. The chromium trioxide ($Cr_2O_3$) of Thakoor is hygroscopic as Thakoor clearly states. A "hygroscopic" is something that attracts water. $Cr_2O_3$ is also a solid. A dielectric does not "attract" water. In fact, if a dielectric did attract water the water itself would damage Appellant's dielectric medium and plurality of nanoconductors disposed in the dielectric medium, so it would not make sense to use a "hygroscopic" material such as that of Thakoor. Chromium trioxide ($Cr_2O_3$) does not tend to concentrate an applied electric field within itself and does not interact with the applied electric field so that charges are redistributed within atoms or molecules of the dielectric.

Additionally, it is important to note that use of H+ ions and the thin film of hygroscopic chromium trioxide in order to achieve the memistor of Thakoor is electrolytic in nature. Thakoor clearly states that the thin film of hygroscopic chromium trioxide ($Cr_2O_3$) serves as a <u>hydrogen ion source</u> (see Page 3132, paragraph under heading "Experimental Details" of Thakoor). The Thakoor device is thus based on an electrolytic configuration, that is, the use of an electrolyte and not a dielectric. Thakoor, for examples, at page 3133, second column, third paragraph, specifically refers to the use of an electrolyte. The memistor of Thakoor is based on the use of the electrochemical process of electrolysis, which is the production of chemical changes by the passage of current through an <u>electrolyte</u> (not a dielectric).

An example of such an electrochemical process is described in the "Introduction" section of Thakoor, Page 3132, Column 1, lines 34 to Column 2, line 2, where Thakoor states that "...in this paper, we report on the operational characteristics and application potential of a solid-state 'memistor," an analog memory device based on the electrochemical ion transport to/from tungsten oxide in a thin-films structure. The three-terminal devices utilizes a reversible transfer of metal (hydrogen) ions in tungsten oxide..." The use of <u>electrolytes</u> is taught, for example on page 3133, column 1, lines 24-26 of Thakoor where Thakoor refers to

"$WO_3$/electrolyte display". The memistor of Thakoor is based on the production of chemical changes by the passage of current through an electrolyte.

An electrolyte is a substance containing free ions which behaves as an electrically conductive medium. Electrolytes are generally composed of ions in a solution of some sort. The use of free ions for a substance that behaves as electrically conductive medium, differs from that of a dielectric, which tends to concentrate an applied electric field (e-field) within itself. This is a fundamental and key difference between Thakoor and Appellant's invention. Unlike an electrolyte, such as that employed by Thakoor, as a dielectric interacts with the applied electric field, charges are redistributed within the atoms or molecules of the dielectric. This redistribution alters the shape of the applied electrical field both inside and in the region near the dielectric material. This is not true of electrolytic materials such as that used to create the memistor of Thakoor. This also not true of the hygroscopic chromium trioxide ($Cr_2O_3$) material of Thakoor, which can produce an acid that is corrosive to Appellant's nanoconductors (e.g., nanotubes, nanowires, DNA, etc.).

Thus, to summarize, Thakoor's device is based on the use of electrolytes, whereas Appellant's device utilizes a dielectric medium in which nanoconductors are free to move about. Additionally, the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor is not used as a dielectric and instead tends to attract water, which would actually damage Appellant's invention as indicated previously. Based on the foregoing, and requirements of establishing inherency as a basis for anticipation, one skilled in the art would not come to the conclusion that the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor inherently anticipates the sue of the dielectric medium of Appellant's invention, because in relying upon the theory of inherency, the Examiner has not provided a basis in fact and/or technical reasoning to reasonably supporting the determination that the allegedly inherent characteristic of the use of a dielectric medium necessarily flows from the teachings of the Thakoor reference. The evidence provided above proves the opposite.

Regarding Appellant's claim for "Hebbian learning" the Examiner argued that Thakoor on page 3133, left column, lines 1-14, "teaches the growing or lessening the conductivity of the resistance put a field to adjust the memory". The Examiner argued that such teaching, to one of ordinary skill in the art, can clearly be a

learning mechanism. The Appellant asks, wow does feature of Thakoor constitute a "learning mechanism"? How is "learning accomplished by "the growing or lessening the conductivity of the resistance put a field to adjust the memory" of Thakoor. Simply adjusting memory is not "learning". Learning is much more sophisticated and complicated process, which is not achieved simply "adjusting memory". Additionally, and even more importantly, how does such a feature of Thakoor inherently anticipate Hebbian learning?

To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of a learning mechanism. Appellant's Hebbian learning mechanism must operate in a very specific manner in order to provide for Hebbian learning. In order to understand what Hebbian learning is, the Appellant believes it would be helpful to provide a brief overview of Hebbian learning.

Hebbian learning is based on Hebbian theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Introduced by Donald Hebb in 1949, it is also called Hebb's rule and is referred to as Hebbian learning as well. Also known as cell assembly theory, the theory is often summarized as *cells that fire together, wire together*, although this is an oversimplification of the nervous system not to be taken literally.

From the point of view of artificial neurons and artificial neural networks, Hebb's principle can be described as a method of determining how to alter the weights between model neurons as a function of their correlations of their activity in time. The weight between two neurons will increase if the two neurons activate simultaneously (they are correlated); it is reduced if they activate separately. Nodes which tend to be either both positive or both negative at the same time will have strong positive weights while those which tend to be opposite will have strong negative weights. It is sometimes stated more simply as "neurons that fire together, wire together."

This original principle is perhaps the simplest form of weight selection. While this means it can be relatively easily coded into a computer program and used to

update the weights for a network, it also prohibits the number of applications of Hebbian learning, at least with respect to software simulations of neural networks. This is because large neural networks contain massive numbers of synapses and the modification of the synapse in the traditional computing paradigm requires accessing memory. This memory access requires extraordinarily more energy than a physical neural network where synaptic states do not have to be "accessed". Today, the term *Hebbian learning* generally refers to some form of mathematical abstraction of the original principle proposed by Hebb. In this sense, Hebbian learning involves weights between learning nodes being adjusted so that each weight better represents the relationship between the nodes. As such, many learning methods can be considered to be somewhat Hebbian in nature.

The following is a formulaic description of Hebbian learning: (note that many other descriptions are possible)

$$w_{ij} = x_i x_j$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$ and $x_i$ the input for neuron $i$. Note that this is pattern learning (weights updated after every training example). In a Hopfield network, connections $w_{ij}$ are set to zero if $i = j$ (no reflexive connections allowed). With binary neurons (activations either 0 or 1), connections would be set to 1 if the connected neurons have the same activation for a pattern.

Another formulaic description is:

$$w_{ij} = \frac{1}{n} \sum_{k=1}^{p} x_i^k x_j^k ,$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$, $n$ is the dimension of the input vector, $p$ the number of training patterns, and $x_i^k$ the $k$th input for neuron $i$. The Appellant invites the Examiner to view the following web site, which contains a good general overview of Hebbian learning:

http://en.wikipedia.org/wiki/Hebbian_learning

Based on a review of Thakoor and a basic understanding of Hebbian learning it is very clear that Thakoor does not provide for any teaching, suggestion or disclosure of Hebbian learning. Additionally, it is very clear that Thakoor does not

inherently anticipate Hebbian learning, and thus the Hebbian learning mechanism provided by Appellant's invention. The Examiner has not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning necessarily flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory".

**Argument 13**

The Examiner asserted that regarding Appellant's claim for Hebbian learning, Thakoor on page 3313, left column, lines 1-14 teaches "the growing or lessening the conductivity of the resistance put a field to adjust the memory". The Examiner further stated that regardless of whether Appellant agrees, such teaching, to one of ordinary skill in the art can clearly be a learning mechanism, i.e., Hebbian learning.

As indicated previously Thakoor on page 3313, left column, lines 1-14 does not provide any hint, suggestion or teaching of a learning mechanism. Thakoor also does not provide any teaching of Hebbian learning.

The Appellant asks, how does Thakoor on page 3313, left column, lines 1-14 provide for a teaching of a learning mechanism as taught by Appellant's invention? Where does the learning take place at Thakoor on page 3133, left column, lines 1-14? How is "learning" accomplished by "the growing or lessening the conductivity of the resistance put a field to adjust the memory" of Thakoor. Simply adjusting memory is not "learning". Learning is much more sophisticated and complicated process, which is not achieved simply "adjusting memory". Additionally, and even more importantly, how does such a feature of Thakoor inherently anticipate Hebbian learning?

To one of ordinary skill in the art, Thakoor on page 3133, left column, lines 1-14, provides no hint, teaching or disclosure of "Hebbian Learning". In fact, Thakoor on page 3133, left column, lines 1-14 also does not clearly provide for a teaching of a learning mechanism. Appellant's Hebbian learning mechanism must operate in a very specific manner in order to provide for Hebbian learning. In order to

understand what Hebbian learning is, the Appellant believes it would be helpful to provide a brief overview of Hebbian learning.

Hebbian learning is based on Hebbian theory, which describes a basic mechanism for synaptic plasticity wherein an increase in synaptic efficacy arises from the presynaptic cell's *repeated* and *persistent* stimulation of the postsynaptic cell. Introduced by Donald Hebb in 1949, it is also called Hebb's rule and is referred to as Hebbian learning as well. Also known as cell assembly theory, the theory is often summarized as *cells that fire together, wire together*, although this is an oversimplification of the nervous system not to be taken literally.

From the point of view of artificial neurons and artificial neural networks, Hebb's principle can be described as a method of determining how to alter the weights between model neurons as a function of their correlations of their activity in time. The weight between two neurons will increase if the two neurons activate simultaneously (they are correlated); it is reduced if they activate separately. Nodes which tend to be either both positive or both negative at the same time will have strong positive weights while those which tend to be opposite will have strong negative weights. It is sometimes stated more simply as "neurons that fire together, wire together."

This original principle is perhaps the simplest form of weight selection. While this means it can be relatively easily coded into a computer program and used to update the weights for a network, it also prohibits the number of applications of Hebbian learning, at least with respect to software simulations of neural networks. This is because large neural networks contain massive numbers of synapses and the modification of the synapse in the traditional computing paradigm requires accessing memory. This memory access requires extraordinarily more energy than a physical neural network where synaptic states do not have to be "accessed". Today, the term *Hebbian learning* generally refers to some form of mathematical abstraction of the original principle proposed by Hebb. In this sense, Hebbian learning involves weights between learning nodes being adjusted so that each weight better represents the relationship between the nodes. As such, many learning methods can be considered to be somewhat Hebbian in nature.

The following is a formulaic description of Hebbian learning: (note that many other descriptions are possible)

$$w_{ij} = x_i x_j$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$ and $x_i$ the input for neuron $i$. Note that this is pattern learning (weights updated after every training example). In a Hopfield network, connections $w_{ij}$ are set to zero if $i = j$ (no reflexive connections allowed). With binary neurons (activations either 0 or 1), connections would be set to 1 if the connected neurons have the same activation for a pattern.

Another formulaic description is:

$$w_{ij} = \frac{1}{n} \sum_{k=1}^{p} x_i^k x_j^k ,$$

where $w_{ij}$ is the weight of the connection from neuron $j$ to neuron $i$, $n$ is the dimension of the input vector, $p$ the number of training patterns, and $x_i^k$ the $k$th input for neuron $i$. The Appellant invites the Examiner to view the following web site, which contains a good general overview of Hebbian learning:

http://en.wikipedia.org/wiki/Hebbian_learning

Based on a review of Thakoor and a basic understanding of Hebbian learning it is very clear that Thakoor does not provide for any teaching, suggestion or disclosure of Hebbian learning. Additionally, it is very clear that Thakoor does not inherently anticipate Hebbian learning, and thus the Hebbian learning mechanism provided by Appellant's invention. The Examiner has not provided a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory".

As far as Appellant's claim for "Hebbian plasticity" or "anti-Hebbian plasticity" is concerned, the Examiner argued that the prior art anticipates this feature in FIG. 2 of Thakoor. The Examiner asserted that FIG. 2 illustrates the variation in resistance with time for several different control voltages. The Examiner asserted

that plasticity by definition is the ability to develop or adapt in response to the environment. The Examiner further stated that "another word, the ability to learn or unlearn". The Examiner also stated that "as responded above regarding Hebbian learning, the growing or lessening the conductivity of the resistance put a field to adjust the memory". The Examiner therefore argued that the learning or unlearning is being performed.

The Appellant respectfully disagrees with this assessment and notes that the arguments provided above against the Examiner's assertions with respect to Argument 2 and the issue of the Hebbian learning mechanism apply equally against the Examiner's assertions with respect to Argument 13. In the interest of brevity, the Appellant will not repeat these arguments, except to point out again that the Examiner has not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor, and in particular, the Examiner's citation of Thakoor on page 3133, left column, lines 1-14, citing "the growing or lessening the conductivity of the resistance put a field to adjust the memory". One of ordinary skill in the art would not see this as teaching or inherently anticipating <u>Hebbian</u> learning. Hebbian learning is a very specific type of neural network learning mechanism, and there is not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian learning <u>necessarily</u> flows from the teachings from Thakoor. Simply "growing or lessening the conductivity of the resistance put a field to adjust the memory" does not inherently anticipate the Hebbian learning mechanism of Appellant's invention.

Regarding "Hebbian plasticity" or "anti-Hebbian plasticity," a review of FIG. 2 of Thakoor does not indicate any suggestion, disclosure and/or teaching of Hebbian plasticity or anti-Hebbian plasticity. The Examiner argued that "plasticity" is the ability to develop or adapt in response to the environment, or the ability to learn or unlearn. This is an oversimplification of a concept that is inherently more complex and sophisticated than the definition provided by the Examiner. FIG. 2 of Thakoor is simply a plot of resistance versus time for several control voltages for a turning the device "on" and "off". Thakoor. FIG. 2 does not suggest, disclose or teach any

sort of "learning" or "unlearning". The Examiner has merely made a statement that FIG. 2 illustrates an ability to learn or adapting to the environment and hence illustrates "learning". FIG. 2 merely describes "turn-on" and "turn-off" characteristics of the Thakoor device, but does not illustrate a device that has the ability to develop or adapt in response to the environment. The Examiner's arguments do not adequately explain how one skilled in the art would identify FIG. 2 as illustrating plasticity and more importantly, Hebbian plasticity or anti-Hebbian plasticity or the performance of any sort of "learning" or "unlearning". Based on the foregoing, the Appellant submits that there is simply not a basis in fact and/or technical reasoning for reasonably supporting a determination that the allegedly inherent characteristic of Hebbian plasticity or anti-Hebbian plasticity flows from the teachings from the test device programming characteristics for variations in resistance of test device with time for several different control voltages of Thakoor's FIG. 2. Thus, FIG. 2 of Thakoor does not anticipate Hebbian and/or anti-Hebbian plasticity, nor learning/unlearning nor even plasticity.

**Argument 14**

Regarding Argument 14, the Examiner asserted that Appellant's argument is merely a general denial of the rejection and does not address the components pointed out by the Examiner. The Examiner stated that "Figure 3 clearly indicates 'a circuit utilizing a $WO_3$, thin film memistor."

The Examiner asserted that as responded above, the "nanoconductors" in Thakoor are "H+ ions". The Examiner argued that Figure 3 of Thakoor anticipates Appellant's claim of an integrated circuit chip utilizing nanotechnology.

The Appellant respectfully disagrees with these assertions. First, the Appellant is not alleging that H+ ions are not on the nanometer scale. The Appellant is asserting, however, that H+ ions and "ions" in general do not constitute nanoconductors/nanoparticles taught by Appellant's invention. In order to understand why such "ions" are not nanoconductors/nanoparticles as taught by Appellant's invention, the Appellant believes that it would be helpful to the Examiner to understand what actually constitutes "nanotechnology". A general discussion of "nanotechnology" is provided in Appellant's "background" section as follows:

"The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. However, it is becoming increasingly difficult to increase the number of elements on a chip using present technologies. At the present rate, in the next few years the theoretical limit of silicon based chips will be reached. Because the number of elements, which can be manufactured on a chip, determines the data storage and processing capabilities of microchips, new technologies are required which will allow for the development of higher performance chips.

Present chip technology is also limited in cases where wires must be crossed on a chip. For the most part, the design of a computer chip is limited to two dimensions. Each time a circuit is forced to cross another circuit, another layer must be added to the chip. This increases the cost and decreases the speed of the resulting chip. A number of alternatives to standard silicon based complementary metal oxide semiconductor ("CMOS") devices have been proposed. The common goal is to produce logic devices on a nanometer scale. Such dimensions are more commonly associated with molecules than integrated circuits.

Integrated circuits and electrical components thereof, which can be produced at a molecular and nanometer scale, include devices such as carbon nanotubes and nanowires, which essentially are nanoscale conductors ("nanoconductors"). Nanoconductors are tiny conductive tubes (i.e., hollow) or wires (i.e., solid) with a very small size scale (e.g., 0.7 to 300 nanometers in diameter and up to 1mm in length). Their structure and fabrication have been widely reported and are well known in the art. Carbon nanotubes, for example, exhibit a unique atomic arrangement, and possess useful physical properties such as one-dimensional electrical behavior, quantum conductance, and ballistic electron transport.

Carbon nanotubes are among the smallest dimensioned nanotube materials with a generally high aspect ratio and small diameter. High-quality single-walled carbon nanotubes can be grown as randomly oriented, needle-like or spaghetti-like tangled tubules. They can be grown by a number of fabrication methods, including chemical vapor deposition (CVD), laser ablation or electric arc growth. Carbon nanotubes can be grown on a substrate by catalytic decomposition of hydrocarbon containing precursors such as ethylene, methane, or benzene. Nucleation layers, such as thin coatings of Ni, Co, or Fe are often intentionally added onto the substrate surface in order to nucleate a multiplicity of isolated nanotubes. Carbon nanotubes can also be nucleated and grown on a substrate without a metal nucleating layer by using a precursor including one or more of these metal atoms. Semiconductor nanowires can be grown on substrates by similar processes."

The aforementioned language generally describes what is meant by "nanotechnology". Of course, it is understood by those in nanotechnology arts that variations to the aforementioned description and examples re: nanotechnology are

likely to arise, but this description can be utilized as a general guideline for the context of "nanotechnology" in which Appellant's invention is provided.

With this in mind, Appellant has provided various examples of nanoconductors in Appellant's specification. For example, the Appellant has referred to nanotubes, nanowires, nanoparticle and even DNA. For example, Appellant's specification at paragraph [0087] indicates that "...Examples of nanoconductors include devices such as, for example, nanowires, nanotubes, and nanoparticles". Appellant's paragraph [0087] also indicates that "The network of nanoconnections depicted in FIG. 3 can be implemented as a network of molecules, including, for example, nanoconductors." Appellant's specification at paragraph [0088) also indicates the following:

> "Nanoconnections 304, which are analogous to biological synapses, can be composed of electrical conducting material (i.e., nanoconductors). Nanoconductors can be provided in a variety of shapes and sizes without departing from the teachings herein. A nanoconductor can also be implemented as, for example, a molecule or groups of molecules."

Thus, Appellant's use of nanotechnology-based devices and components relates to multi-atom structures that are built (man-made or natural) or synthesized. DNA, for example, is a naturally constructed multi-atom structure. Free floating ions are not such structures. Atoms and atomic ions do not represent nanoparticles/nanoconductors because "nanotechnology" seeks to use atoms as the building blocks of multi-atom structures. In this light, the H+ ion of Thakoor is not a nanoconductor as taught by Appellant's invention, but rather simply just that -- an ion. Thus, it is not proper to identify the ions of Thakoor as anticipating the nanoconductors of Appellant's invention because one skilled in the art would not recognize an ion as constituting such a nanoconductor (i.e., built or synthesized multi-atom structures such as DNA, nanotubes, nanowires, etc). The ions of Thakoor do not inherently anticipate the nanoconductors taught by Appellant's invention because the Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of nanoconductors (as taught by Appellant's invention) necessarily flows from the teachings of the applied prior art, i.e., Thakoor and the H+ ions.

The Appellant also notes that as indicated previously, the thin-film memistor of Thakoor is neither a synapse nor a physical neural network, but is a device that complements a neuron. The memistor of Thakoor does not inherently anticipate the synapse and/or physical neural network taught by Appellant's invention because the Examiner has not provided a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic of a physical neural network and/or synapse (as taught by Appellant's invention) necessarily flows from the teachings of the applied prior art, i.e., the thin film memistor device.

**Argument 15**

Regarding Argument 15, the Examiner attempted to remind the Examiner that the Thakoor reference teaches all of the clam limitations of the claims from which claims 8 and 12 depend. The Appellant already has provided evidence that this is not the case. Thakoor does not teach the physical neural network, the dielectric medium, the nanoconductors, the Hebbian learning mechanism and other features of Appellant's invention. There is simply no disclosure and teaching of ALL of these claim limitations in Thakoor. The Examiner argued, however, that Thakoor is properly combined with Srivastava as a basis for a rejection to claims 8 and 12 under 35 U.S.C. 103.

The Examiner directed the Appellant to page 10 of the Office Action where the teaching or suggestion to make the combination is found within the prior art itself. (Yes, but where is the teaching or suggestion found in the prior art?)

Regarding the Appellant's argument that the Office Action has not provided an explanation of a "reasonable expectation of success", the Examiner argued that MPEP 2143 does not require the Examiner to provide an explanation, but instead stated that "Appellants may present evidence showing there was not a reasonable expectation of success."

There is plenty of evidence found in the prior art references cited by the Examiner to demonstrate that there is not a reasonable expectation of success for combining the references as argued by the Examiner. First, combining the carbon nanotubes of Srivastava with Thakoor would mean somehow injecting or combining

(which is not event hinted at in either reference how this would be accomplished) such nanotubes into or with the hygroscopic chromium trioxide ($Cr_2O_3$) of Thakoor. Thakoor also teaches that the $Cr_2O_3$ is used by Thakoor as a hydrogen ion source. The Appellant further again notes that chromium trioxide is a solid. How would such nanotubes be successfully combined with such a solid? The chromium trioxide ($Cr_2O_3$) of Thakoor is hygroscopic as Thakoor clearly states. A "hygroscopic" is something that attracts water. $Cr_2O_3$ is also a <u>solid</u>. A dielectric does not "attract" water. In fact, if chromium trioxide were mixed with water, it would form a strong acid that would corrode the nanotubes of Srivastava. If the nanotubes of Srivastava would be corroded by the resulting acid of Thakoor, why would one skilled in the art be motivated to combine Thakoor with Srivastava? Additionally, where is the suggestion in either Srivastava or Thakoor that such nanotubes could be combined with a solid such as that of chromium trioxide to provide for the essential claim elements of Appellant's invention of nanoconductors that are <u>free to move about</u> in a dielectric medium? How can the nanotubes of Srivastava freely move about in the solid chromium trioxide of Thakoor?

Combining nanotubes to freely move about in such a solid would be very difficult based on a reading of both the Srivastava and Thakoor references. Chromium trioxide is a dark-red, odorless flakes or powder. Thus, it is a solid. More importantly, chromium trioxide is an acid and is often referred to as chromic acid. Ethanol, for example, will ignite on contact with it. What happens when the nanotubes of Srivastava are combined with the chromic acid of Thakoor? The Examiner has not addressed this issue. The resulting acid of hygroscopic chromium trioxide will corrode the nanotubes of Srivastava and renders them useless. One skilled in the art would realize this. As such, Appellant submits that there is simply no reason or motivation for one skilled in the art to combine the references as argued by the Examiner to provide for a teaching of all of the claim limitations of Appellant's invention.

## SUMMARY OF ARGUMENTS AND CONCLUSION

The appealed claims are not taught by either Thakoor or Srivastava.

Appellants respectfully submit that their arguments as well as the specification and prosecution record support that the Group I and II claims are allowable.

Appellants now respectfully request that the Board reverse the rejections of the Group I and II claims and instruct the Examiner to allow such claims.

Respectfully submitted,

Kermit Lopez

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Kermit Lopez
Attorney for Appellant
Registration No. 41,953
ORTIZ & LOPEZ, PLLC
P.O. Box 4484
Albuquerque, NM 87196-4484

## X. APPENDIX

The following Appendix (X) provides a listing of the appealed claims:

1. A system, comprising:

a physical neural network configured utilizing nanotechnology, wherein said physical neural network comprises a plurality of nanoconductors suspended and free to move about in a dielectric medium and which form neural connections between pre-synaptic and post-synaptic components of said physical neural network; and

a learning mechanism for applying Hebbian learning to said physical neural network.

2. The system of claim 1 wherein said learning mechanism utilizes a voltage gradient to implement Hebbian plasticity within said physical neural network.

3. The system of claim 1 wherein said learning mechanism utilizes voltage gradient dependencies associated with physical neural network to implement Hebbian learning within said physical neural network.

4. The system of claim 1 wherein said learning mechanism utilizes pre-synaptic and post-synaptic frequencies to provide Hebbian learning within said physical neural network.

5. The system of claim 1 wherein said learning mechanism utilizes a voltage gradient to implement anti-Hebbian plasticity within said physical neural network.

6. The system of claim 1 wherein said learning mechanism utilizes voltage gradient dependencies associated with physical neural network to implement anti-Hebbian learning within said physical neural network.

7. The system of claim 1 wherein said learning mechanism utilizes pre-synaptic and post-synaptic frequencies to provide anti-Hebbian learning within said physical neural network.

8. The system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanotubes.

9. The system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanowires.

10. The system of claim 1 wherein said plurality of nanoconductors includes nanoconductors comprising nanoparticles.

11. A system, comprising:

a physical neural network configured utilizing nanotechnology, wherein said physical neural network comprises a plurality of nanoconductors suspended and free to move about in a dielectric medium and which form neural connections between pre-synaptic and post-synaptic components of said physical neural network; and

a learning mechanism for applying Hebbian learning to said physical neural network wherein said learning mechanism utilizes a voltage gradient or pre-synaptic and post-synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within said physical neural network.

12. The system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanotubes.

13. The system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanowires.

14. The system of claim 11 wherein said plurality of nanoconductors includes nanoconductors comprising nanoparticles.

15. The system of claim 11 wherein said dielectric medium comprises a dielectric liquid.

16. The system of claim 15 wherein said plurality of nanoconductors form physical neural connections when said dielectric medium is exposed to an electric field, such that said physical neural connections can be strengthened or weakened depending

upon a strengthening or weakening of said electric field or an alteration of a frequency thereof.

17. A system, comprising:

a plurality of molecular conductors disposed in and free to move about within a dielectric medium comprising a dielectric solvent or a dielectric solution;

at least one input electrode in contact with said dielectric medium; and

at least one output electrode in contact with said dielectric medium, wherein said plurality of molecular conductors form physical neural connections when said dielectric medium is exposed an electric field across said at least one input electrode and said at least one output electrode, such that said physical neural connections can be strengthened or weakened depending upon a strengthening or weakening of said electric field or an alteration of a frequency thereof.

18. The system of claim 17 further comprising a physical neural network comprising said plurality of molecular conductors disposed within a dielectric medium comprising a dielectric solvent or a dielectric solution, said at least one input electrode in contact with said dielectric medium, and said at least one output electrode in contact with said dielectric medium.

19. The system of claim 18 further comprising a learning mechanism for applying Hebbian learning to said physical neural network wherein said learning mechanism utilizes a voltage gradient or pre-synaptic and post-synaptic frequencies thereof to implement Hebbian or anti-Hebbian plasticity within said physical neural network.

20. The system of claim 18 wherein said physical neural network is configured as an integrated circuit chip utilizing nanotechnology.

## XI. EVIDENCE APPENDIX

Not Applicable

## XII. RELATED PROCEEDINGS APPENDIX

Not Applicable